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Effect of Irrigation Technologies That Are Managed at Household Level on Farm-Incomes: An Experience from Charco-Dam Users in Nzega, Tanzania

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Abstract

Background: In arid and semi-arid areas, investing in water-related technologies is expected to affect productivity and eventually increase farm incomes. However, there is a limitation of empirical evidence on the effects of irrigation technologies managed and controlled at the household level on farm incomes. This study was interested in studying the effect of adopting Charco-Dam Technology (CDT) as one of the small-scale rainwater harvesting on-farm incomes. **Methods:** The study used the Propensity Score Matching (PSM) method to empirically prove the effect of the CDT on the farm incomes using 528 small-scale vegetable producers (220 are adopters of CDT and 308 are non-adopters) from Nzega District, located in Tabora Region, Tanzania. **Results:** Generally, CDT was found to improve farm incomes, which is the key objective of various strategies and policies toward agricultural development in Tanzania. **Conclusion:** In due respect, it is high time for the governments, farmers themselves, and other agricultural development partners to seize the opportunity to have such technologies to reap their potential benefits. Therefore, the study recommends that the agricultural departments of local governments and all agricultural stakeholders encourage the uptake of such technologies, especially among small-scale farmers in arid and semi-arid areas.

Keywords

Charco-Dam Technology, Farm Incomes, Irrigation Technologies, Propensity Score Matching, Small-Scale Vegetable Producers

1. Background

Agricultural technology adoption is expected to positively affect agricultural outputs (Brookes & Barfoot, 2018; Ogada et al., 2014; Rehman et al., 2017; Thompson & Gyatso, 2020). Moreover, an increase in agricultural outputs is associated with improved farm incomes and eventually improves farming households' well-being (Brookes & Barfoot, 2018; Ding et al., 2011; Hailu et al., 2014; Lokina et al., 2011). Various agricultural technologies have various effects on the farm incomes; these depend on how much the factors that affect the adoption of the technologies also affect crop yield and, eventually, farm incomes (Anang et al., 2016; Awotide et al., 2013; Diiro, 2013). Adoption of any intervention must be geared towards the benefits that one is deriving from the intervention. Farm income is one of the benefits that a farmer expects from any farming investment. In arid and semi-arid areas, investing in water-related technologies is expected to affect productivity and eventually increase farm incomes. However, there is limited empirical evidence on the effects of the irrigation technologies managed and controlled at the household level on farm incomes.

Charco-dam Technology (CDT) has been used in Tanzania for decades through government efforts and/or support from development partners and non-governmental organizations. This technology is one of the small-scale rainwater harvesting technologies that fall under dams, ponds and pans, which can be managed and controlled at either communal or household level (Mati, 2012, 2015; Nissen-Petersen, 2006). Its management and control are mainly determined by; the nature of its establishment (design and size), ownership (private or public) as well as the nature of users/beneficiaries (livestock, crops or human consumption) (Awulachew et al., 2005; Gomez et al., 2018; Nissen-Petersen, 2006; Stephens, 2010).

In Tanzania, such dams are known as "*Malambo*" in Swahili (the language used by most Tanzanians). These dams are managed and controlled at the household level, and they are mainly established for livestock and crops. Due to the challenges brought by the communal managed and controlled water sources (which include limited frequency and amount of water accessed), farmers in Nzega decided to adopt the CDT to overcome the shortage of irrigation water. Despite its advantages in terms of; simplicity in architectural design, management and control of the water, and its practical usefulness in reducing water shortage, CDT has been rarely adopted among small-scale farmers in Nzega district. So far, various studies in East Africa and Tanzania, in particular, have been provided information on the; typologies, best practices, profitability, designs, affordability and cost of investing in various RWH techniques (AgWater Solution, 2010; Gowing et al., 1999; Hatibu et al., 2006; Hatibu & Mahoo, 2000; Mahoo et al., 2007; Nissen-Petersen, 2006; Rwehumbiza, 2007; Senkondo et al., 1998, 2004; Studer & Liniger, 2013). There is limited information about the socio-economic and socio-demographic dynamics behind the adoption of these RWH technologies, their contribution to small-scale farm production efficiencies, and their ef-

fectiveness on farm incomes, particularly for those technologies managed and controlled at the household level. This is not only in Nzega district but also in other semi-arid areas in the country and across the East Africa region.

Therefore, this study was interested in studying the effect of adopting Charco-dam technology as one of the small-scale rainwater harvestings, on-farm incomes and gaining further understanding of the empirical verification of the effect of adoption also other dynamics alongside the adoption of the technology and farm incomes. This study took a case on small scale vegetable producers in Nzega district, Tanzania.

2. Conceptual Framework

The fundamental objective of this study was to estimate the effect of CDT on farm incomes. According to Cochran & Chambers (1965), as further clarified in Austin (2011), these types of estimation involve elucidating causal-effect relationships in settings in which it is not feasible to use controlled experimentation. This is because the treated group and untreated group (for this case, referred to as adopters and non-adopters of CDT) can have different unobservable characteristics even in the absence of treatment effect.

Agricultural technology is a specific instrument designed to facilitate production in agricultural activity. It is an action designed to facilitate or improve pre-existing means of agricultural production. Therefore, agricultural technology is one of the resources in agricultural production (Chi & Yamada, 2002). Suppose the objective of the farming community is to increase agricultural production. In that case, agricultural technology adoption is the key instrument instead of the simple expansion of agricultural land, which might be hazardous to environmental conservation. In support of this, several studies have shown that sufficient agricultural technologies are available in developing countries to boost productivity. Although literature points out sufficient agricultural technologies in Sub-Saharan Africa to increase food production an appropriate policy environment coupled with an active technology transfer program has been lacking (Byerlee et al., 1994, as cited in Makokha et al., 2001). To improve this, several studies have been conducted suggesting the importance of agricultural technologies for better agricultural productivity.

Conceptually, if ith individual farmer adopts a particular agricultural technology at time t, then farm-income for i at $t+1$ is Y_{1i}, also if ith individual farmer did not adopt a particular agricultural technology at time t, then farm income for i at $t+1$ is Y_{0i}. So, the effect of adoption is simply denoted as $Y_{1i} - Y_{0i}$ Caliendo and Kopeinig (2008) refer to this as Roy-Rubin Model, which focuses on three key aspects: an individual, the treatment, and the potential outcome. Since it is impossible for Y_{1i}, and Y_{0i} to occur simultaneously, then it is difficult to have unbiased estimates of counterfactual model for individual treatment effects. To overcome the problem, calculation of aggregate treatment effects is required (Morgan & Winship, 2015). There are two major aggregate

treatment effects, namely the average treatment effect (ATE) and the average treatment effect on the treated group (ATT). ATE is the average effect that would be observed if everyone in the treated and the control groups received treatment, compared with if no one in both groups received treatment, while ATT is the average difference that would be found if everyone in the treated group received treatment compared with if none of these individuals in the treated group received treatment (Harder et al., 2010). Given that treatment and control groups in observational studies may not be comparable, then ATT is recommended over ATE (Imbens, 2004; Winship & Morgan, 1999), and thus it has been employed in this study.

3. Research Design, Data and Methods

3.1. Research Design and Sampling

This study used a cross-sectional research design. This was preferred because it allows the collection of primary data at a single point in time, especially where the population is large. The study used a descriptive survey design, and the design was preferred because it allows analysis of both quantitative and qualitative data (Cohen et al., 2005, 2006, 2016, 2020; Levin, 2006; Setia, 2016; Wang & Cheng, 2020). A descriptive survey also helps to describe the characteristics of targeted individuals or groups. In the first stage, the district, the wards (5) and the villages (5) were purposefully selected. The criteria for selection were based on the presence of Charco-dam technology and the nature and type of crops cultivated. Secondly, through the respective ward and village Extension Officers, the number of small-scale vegetable producers in each village was identified such that, Itunda = 102, Ikindwa = 138, Shila = 152, Busondo = 173 and Iyombo = 184, and the list comprised both adopters and non-adopters of the Charco-Dam Technology (CDT) was prepared. Thirdly, using the formula by Yamane (2001), a number of respondents for each village were randomly selected. However, due to incompleteness and missing of information for some of respondents, 528 (220 adopters and 308 non-adopters) were used for analysis.

3.2. Data and Variables

Data from respondents (adopters and non-adopters of Charco-dam technology) were gathered using a semi-structured questionnaire. Moreover, a total of six focused group discussions (FGDs) were conducted to validate and substantiate the data collected from individual interviews. One FGD was conducted at council headquarters and five at the village level, guided by a checklist. The variables used to estimate the logit model was the dichotomous variable "usecdt", which represents the independent variable (1 if respondent adopted CDT, and 0 otherwise), sex of respondent (1 if male and 0 otherwise), household head formal education (1 if the household head has formal education and zero otherwise), a number of people residing in the household (log of the land size used to cultivate vegetables in acres), household's source of labour for the Charco-dam related ac-

tivities (1 if the labour if from the family and zero otherwise), household head's membership to microfinance scheme (1 if he/she is a member and zero otherwise), and membership to community development groups (1 if he/she is a member and zero otherwise).

3.3. Estimation Methods

Estimation of Adoption Effects on Farm-Incomes

Farm incomes are regarded as the average gross income generated from crop sales. In a typical farming household, at *Ceteris Paribus*, an increase in crop production goes hand-in-hand with an increase in farm incomes, which altogether increase the overall incomes of the farming households and eventually improve their living standards (Christiaensen et al., 2006; Hailu et al., 2014; Isoto et al., 2014). Therefore, in estimating treatment effects on the treated (ATT), the study assumed "*treatment*" to be the adoption of Charco-dam technology (CDT); the "*treated*" being individual small-scale vegetable farmers, and; the "*effect*" is the change (increase or decreasing) of the farm-incomes for the farmers who adopted the CDT. So, the ATT model is denoted as:

$$\text{ATT} = E\left(y_{1i} - y_{0i} \big| A_i = 1\right) = E\left(y_{1i} \big| A_i = 1\right) - E\left(y_{0i} \big| A_i = 1\right) \tag{1}$$

Knowing that an individual can only adopt or not adopt and not both, the major concern was to deal with unobservable values of $E\left(y_{0i} \big| A_i = 1\right)$ in equation (1), as it is very difficult to have unbiased estimates for the treatment effects in such a situation; this is due to lack of randomness when subjecting assignments to the treatment and control group, thus overcoming the weakness, the matching method is normally recommended. A Propensity Score Matching (PSM) method can provide the required solutions; this approach uses a special procedure that uses propensity scores and a matching algorithm to calculate the causal effect (Li, 2013). Allowing reconstruction of counterfactuals using observational data and the ability to overcome distribution overlap between the two group samples are the two important advantages of using PSM over the other causal-effect estimating methods (Imbens, 2004; Winship & Morgan, 1999). However, if using a few samples, there is a threat of losing some of the treatment group members who may carry important aspects of the study. Hence a large sample is recommended when using this type of method (Rubin & Thomas, 1996; Sainani, 2012; Streiner & Norman, 2012).

Estimation of Propensity Score Matching

Following the work of Rosenbaum and Rubin (1983), as explained in Becker and Ichino (2002), PSM is considered as the conditional probability of receiving a treatment given pre-treatment characteristics, which is noted as:

$$p(X) \equiv \text{Pr}\left\{A_i = 1 \big| X\right\} = E\left\{A_i \big| X\right\} \tag{2}$$

where $A_i = \{0,1\}$ representing the adoption of Charco-dam technology, and X is the vector multidimensional pre-treatment characteristics. If the exposure to

treatment is random within elements of X, then it is also random within the element of mono-dimensional variable $p(X)$. Therefore, ATT of the *labour* population with a propensity score $p(X_i)$, can be written as:

$$\begin{aligned}
\text{ATT}_i &\equiv E\{Y_{1i} - Y_{0i} | A_i = 1\} \\
&= E\{E\{Y_{1i} - Y_{0i} | A_i = 1, p(X_i)\}\} \\
&= E\{E\{Y_{1i} | A_i = 1, p(X_i)\} - E\{Y_{0i} | A_i = 0, p(X_i)\} | A_i = 1\}
\end{aligned} \tag{3}$$

whereby; the outer expectation is over the distribution of $p(X_i) | A_i = 1$ while Y_{1i} and Y_{0i} are the potential outcomes in the two counterfactual situations of treatment and no-treatment, respectively. However, for this to be valid, two assumptions must be satisfied that is; the Balancing assumption, which assumes that if $p(X)$ is the propensity score, then $A_i \perp X | p(x)$; as well as the Unconfoundedness assumption, which assumes that, if assignment to treatment is unconfounded, i.e. $Y_{1i}, Y_{0i} \perp A_i | X$, then, assignment to treatment is unconfounded given the propensity score, i.e. $Y_{1i}, Y_{0i} \perp A_i | p(x)$ (Rosenbaum & Rubin, 1983). Further, Becker and Ichino (2002) clarify that, if the balancing assumption is satisfied, observation within the same propensity score must have the same distribution of observable and unobservable characteristics independently of treated status, meaning that the exposure to treatment is random and thus treated and control units are technically observational identical. Estimating Propensity Score Matching involves several steps (**Figure 1**). At each step, various decisions must be made regarding the choice of covariates, models for creating propensity scores, matching distances and algorithms, the estimation of treatment effects, and diagnosing the quality of matches (Caliendo & Kopeinig, 2008; Gu & Rosenbaum, 1993; Ho et al., 2007; Stuart, 2010; Stuart & Rubin, 2008).

However, algorithms in these steps can be restricted to the common support. Refer to Equation (3); this restriction assumes that for every unit with $A_i = 1$, there should be a unit with the same (or a similar) value of $p(X_i)$ among the group of units with $A_i = 0$, meaning that the test of the balancing property is performed only on the observations whose propensity score belongs to the intersection of the supports of the propensity score of treated and controls. Imposing this condition normally improves the quality of the matches used to estimate the ATT (Becker & Ichino, 2002; Lechner & Strittmatter, 2017).
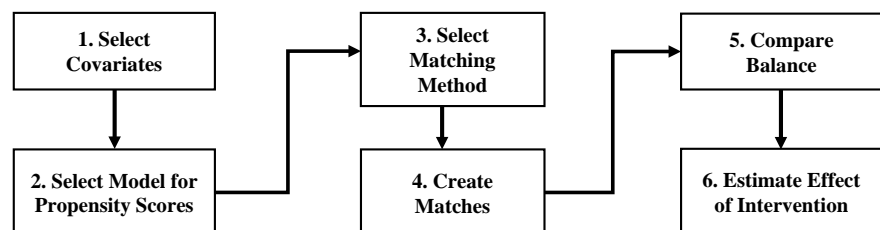

Figure 1. Steps in propensity matching process. Source: Adopted from Harris & Horst (2016).

Choosing Matching Algorithm

Various literature has suggested a number of the matching algorithm (Becker & Ichino, 2002; Brazauskas & Logan, 2016; Caliendo & Kopeinig, 2008; Jacovidis, 2017; Li, 2013; Sainani, 2012; Stone & Tang, 2013). Given the fundamental objective of the study, which is to measure the effect of adoption on the farm-incomes, then two matching estimators, that is the Nearest Neighbour Matching (NNM), and the Kernel Matching Method (KMM), were used for this analysis. In the case of NNM, the ATT are computed by selecting n comparison units whose propensity scores are nearest to the treated unit in question, meaning that the outcome of the control units matches with the outcome of the treated units only when the propensity scores fall in the predetermined radius of the treated unit, thus can also referred as radius matching (Caliendo & Kopeinig, 2008; Li, 2013). For KMM, this estimation uses a weighted average of all controls obtained by the distance of propensity score, bandwidth parameter, and Kernel function. According to Li (2013), these aspects can be specified by the Gaussian Kernel formula.

4. Results and Discussion

4.1. Results

Logit estimation result

Generally, the results from logit estimation of propensity scores in Table 1 show that the model is very significant as expressed by LR chi-square test (9) = 344.12 at 1% level and Pseudo R^2 = 0.4798. Despite the fact that the value of Pseudo R^2 is less than 50%, there is no doubt about the relevance of the variables used in the model; according to Smith and McKenna (2013), there is no existing guideline for interpreting the value of Pseudo R^2 in logistic regressions. Further, the data used have been better predictors of adoption choice, as six out of nine variables in the model were statistically significant. Further, Table 2 shows that household size, log of land size, membership in micro-credit scheme, and membership in community development groups positively influence the likelihood of adopting CDT, both at a 1% level of significance. While, land tenure and use of only family labour negatively affected the likelihood of adopting CDT at 1% and 5% levels of significance, respectively. Since the output of the logit model will be used to analyze matching and impact estimation, these results cannot be further discussed in this section, rather will be explained in the propensity score analysis in the next sections.

Balancing of the Propensity Scores

To ensure that the distribution has a good match to facilitate the comparison, a balancing of the scores was conducted to ensure a balance of the scores within the common support region. Using Becker and Ichino's (2002) approach, the scores outside the common support restriction were not considered, remaining with the data lying between 0.0011265 and 0.9991747 (Table 3).

Distribution of the Propensity Scores

Table 1. Description of variables used in adoption models.

Variable		Description
Dependent Variable		
Usecdt (*Adoption Model*)		1 if respondent used charco-dam technology to irrigate his/her crops; 0 otherwise
Independent Variables		
Sexhead	α_1	Sex of household head, 1 if the respondent is a male; 0 otherwise
Agehead	α_2	Age of household head in years
Eduhead	α_3	Household head's formal education
Hhinc	α_4	Household income in Tanzania Shillings (TZS)
Hhsize	α_5	Number of people residing in the household
Landten	α_6	Land tenure; 1 if farm-land is owned by the respondent; 0 otherwise
MemberFin	α_7	Household head's membership to micro-finance scheme; 1 if yes; 0 otherwise
Lnlandsize	α_8	Log of the land size used to cultivate vegetables in acres
SourceLabour	α_9	Household's source of I for the Charco-dam related activities, 1 if the family I only; 0 if otherwise
NoLabourFA	α_{10}	Number of individuals provided labour for farm activities
MemberDeve	α_{11}	Household head's membership to community development groups in the village/ward; 1 if yes; 0 if no

Table 2. Logit estimation of propensity score.

Dependent Variables; Adoption of CDT (1 if respondent used charco-dam technology [CDT] to irrigate his/her vegetables; 0 otherwise)

Independent Variables;	Coef.	Std. Err.	Z	$P > |z|$
Constant	−6.69	0.90	−7.44	0.000***
Sex of household head (1 = Male, 0 = Female)	0.52	0.40	1.31	0.191
Age of household head (in years)	−0.01	0.01	−0.76	0.447
Education of household head (1 = formal, 0 = otherwise)	−0.29	0.38	−0.76	0.447
Household size	1.00	0.10	9.70	0.000***
Land tenure (1 = own land, 0 = otherwise)	−0.82	0.29	−2.85	0.004***
Log of land size	1.49	0.29	5.11	0.000***
Labour (1 = family labour only, 0 = family and hired labour)	−0.62	0.27	−2.26	0.024**
Membership to microfinance scheme (1 = yes, 0 = no)	0.85	0.28	3.01	0.0030***

Continued

Membership to community development groups (1 = yes, 0 = no)	1.02	0.28	3.68	0.0000***
Number of Observation	528			
LR chi2 (9)	344.12			
Prob > chi2	0.0000			
Pseudo R²	0.4798			
Log-likelihood	−186.554			

*** and ** represent significance at 1% and 5% levels. Source: Research Data, 2018.

Table 3. Description of the estimated propensity scores in the region of common support.

Estimated Propensity Score				
	Percentiles	Smallest		
1%	0.0018394	0.0011265		
5%	0.0073445	0.0014887		
10%	0.0207809	0.0015290	Obs	528
25%	0.0746100	0.0017890	Sum of Wgt.	528
50%	0.3096342		Mean	0.4166667
		Largest	Std. Dev.	0.3633590
75%	0.7943097	0.9968558		
90%	0.9656897	0.9969385	Variance	0.1320298
95%	0.9873150	0.9984800	Skewness	0.4126149
99%	0.9962763	0.9991747	Kurtosis	1.5811910

Source: Research Data, 2018.

This presents the distribution of the generated propensity scores among adopters and non-adopters of CDT. The distribution balanced estimated propensity scores, as portrayed in **Figure 2**, show that more scores for non-adopters of CDT were concentrated to the left of the 0.5 mark (left-skewed), while the highest point was very close to zero. On the other hand, the scores for adopters of CDT were concentrated to the right of the 0.5 mark (right-skewed), while the highest point was very close to 1. However, most of the scores are concentrated in the middle of the two extremes; this indicates there is a balance of the score between the two groups, which will be confirmed by balancing property in the coming section.

Identification of Optimal Number of Blocks

Identifying the optimal number of blocks concluded with five blocks; these blocks ensure the mean propensity score is not different among the treated and control groups. The balancing property in this analysis is satisfied. Final blocks are defined, and the common support option has been selected (**Table 4**).
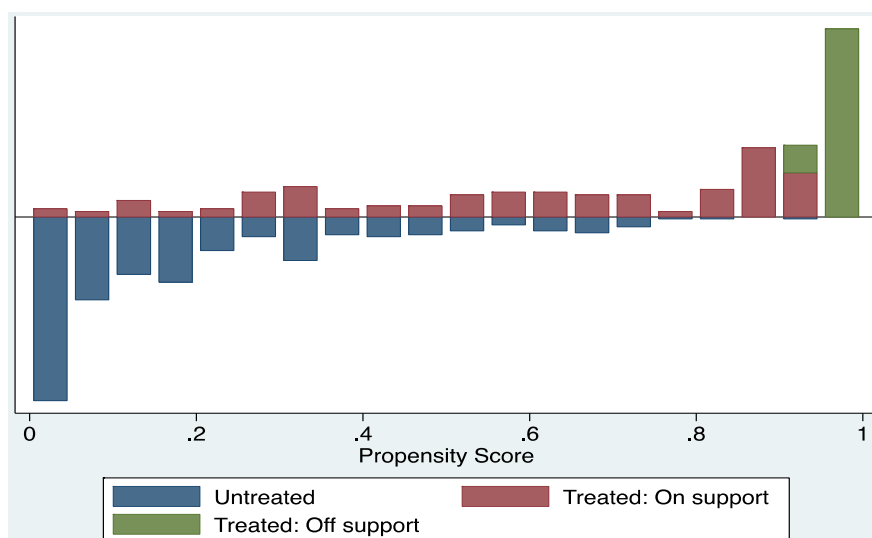
Figure 2. Distribution of balanced estimated propensity scores. Source: Research Data, 2018.

Table 4. Distribution of adopters and non-adopters of CDT based on blocks of propensity score.

Inferior of Block of Propensity Score (with common support)	Use of Charco-Dam Technology		
	Non-adopter	Adopters	Total
0.0011265	209	14	223
0.2	50	28	78
0.4	27	20	47
0.6	21	28	49
0.8	1	130	131
Total	308	220	528

Source: Research Data, 2018.

Effect of CDT Adoption on Farm-Incomes

To obtain the actual effects of the adoption of CDT on farm incomes, the average treatment on the treated (ATT) was employed to measure the effect using Nearest Neighbour Matching (NNM), the most common matching algorithm. Literature suggests that NNM is the most straightforward matching estimator, whereby the individual from the comparison group is chosen as a matching partner for a treated individual closest to the propensity score (Caliendo & Kopeinig, 2008; Stuart, 2010). Furthermore, Austin (2014) and Harris & Horst (2016) concluded that NNM without replacement results in estimates with minimal bias compared to other algorithms. However, to check the robustness of the results, the Kernel-Based Matching method (KBM) was used. Following the work of Li (2013), this method matches all treated units with a weighted average of all controls.

Nearest Neighbour Methods (NNM)

Table 4 compares adopters and non-adopters farmers matched by the Nearest-Neighbour Matching Method (NNM). Two hundred twenty adopters of CDT are matched with 67 non-adopter. Further, Table 5 indicates that the adoption of CDT has a significant positive effect on farm incomes. The ATT estimated by the NNM method suggest that CDT adopters have, on average 549,000/ = TZS per year higher in farm incomes than non-adopters. This difference in farm income is statistically significant at the 1% level.

Kernel Matching Method (KMM)

To determine the robustness of the results, the Kernel Matching Method (KMM) was applied. Table 6 shows results obtained by KMM. Standard errors are obtained by bootstrapping using 50 replications because analytical standard errors could not be computed. The 220 CDT adopters were matched with 308 non-adopters. The ATT estimated by the KMM method suggest that CDT adopters have, on average 597,000/ = TZS higher in farm incomes than non-adopters. These results are statistically significant and have the same direction as the results obtained by the NNM method.

Further, the study assumed no selectivity bias and then analyzed the effect of CDT adoption on farm incomes using the Ordinary Least Square (OLS) method. Compared to results from matching methods NNM and KBM, results by the OLS method are similar in terms of the sign and significance with NNM and KMM, but with a slight difference in magnitude as adopting CDT was observed to increase the farm incomes by 465,514.40/ = TZS (Table 7).

4.2. Discussion

The relationship between agricultural technology adoption and improved farm

Table 5. Average treatment effects on the treated (ATT) using NNM.

Method	Outcome	ATT	Std Error	t-value	No. of Treated	No. of Control
NNM	Farm income	549000***	298,000	1.842	220	67

***Significant at 1% level. Source: Research Data, 2018.

Table 6. Average treatment effects on the treated (ATT) using KMM.

Method	Outcome	ATT	Std Error	t-value	No. of Treated	No. of Control
KMM	Farm income	597000***	101,000	5.910	220	308

***Significant at 1% level. Source: Research Data, 2018.

Table 7. Average effects of CDT on the treated (OLS Method).

Method	Outcome	Effect	Robust Std Error	t-value	No. of Treated	No. of Control
OLS	Farm income	465514.40***	65564.58	7.10	220	308

***Significant at 1% level. Source: Research Data, 2018.

income is hypothesized to be straightforward. Thus, the bigger challenge in this study was to prove whether changes in farm incomes were attributed to CDT adoption. However, the variations in socio-demographic, socio-economic, and farm characteristics among farmers can influence the adoption of agricultural technology, which can also do to farm-outputs and eventually affect the farm incomes.

The observed effect of the adoption of CDT on farm incomes might be perceived less or more by some individuals compared to their total household incomes (on-farm + off-farm), but the fact that the findings are positive and significant has its particular importance. The perceived effect on farm incomes (less or more) could be because there might be some challenges on the determinants for farm incomes beyond socio-economic and farm-level characteristics. For instance, despite the fact that market forces determine the price of the agricultural outputs, the perishability of the vegetables can influence their price and hence affects the farm incomes. Moreover, the vegetables produced, which are assumed to account for the farm incomes, can encounter various post-harvest challenges before reaching the final consumer (Abera et al., 2020; Rahiel et al., 2018), hence influencing the quantity purchased and eventually farm incomes. All such situations can influence the magnitude of the farm incomes.

5. Conclusion

This study analyzes the effect of small-scale irrigation technologies managed at the household level on household income, taking an experience of Charco-dam users in Nzega District, Tanzania. It was found that there is a positive relationship between adopting CDT and an increase in farm income, meaning that Charco-dam users had improved productivity and eventually farm incomes as compared to non-users of the technology. On the other hand, Propensity Score Matching (PSM) results revealed that large farm size attracts the adoption of CDT, which increases crop production and yield and eventually increases farm income. Therefore, it is recommended that the agricultural departments at local government authorities, together with all agricultural stakeholders in arid and semi-arid areas, encourage the uptake of such technologies, especially among small-scale farmers. This is an important strategy to increase farm incomes among typically small-scale farming households and hence improve their well-being.

Acknowledgements

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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