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An Assessment of the Impact of Rainwater Harvesting Ponds on Farm Income in Rwanda

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Abstract

Rainwater harvesting is increasingly seen as a strategy for enhancing agricultural productivity and boosting farm income in many drought prone areas. While extensive efforts are going on in constructing and providing smallholder farmers with water harvesting structures, such as ponds in Rwanda, there is limited knowledge of the factors that influence adoption of such structures and their impact on households' input use and farm income. This study applied propensity score matching technique to assess the impact of rainwater harvesting ponds on farm income of small scale farmers in Rwanda. The study also assesses the factors that influence adoption of rainwater harvesting ponds by using a binary logit model. Results show that households with rainwater harvesting ponds are significantly better off in terms of achieving higher income than those without ponds, even though they are comparable in essential household characteristics. The study finds that household size, physical and financial asset endowments, group membership are significant in explaining the household decision to adopt rainwater harvesting ponds. It discusses the implications of these findings for policy.

Key words: *Rainwater harvesting ponds, impact assessment, Propensity Score Matching, adopters (smallholder farmers in Rwanda).*

Introduction

Conservation of the environment and sustainable utilization of land and water resources have remained one of the major policy issues of concern in many developing regions (Bekele et al.2007). Although, Rwanda is known as an equatorial country with high rainfall; poor water management, low soil fertility, unreliable and erratic rainfall have continued to threaten food production in major arid and semi-arid regions of the country (MINAGRI 2007).Land degradation is a serious environmental problem worldwide and a major threat to the sustainability of agriculture and economic development. It has further decreased agricultural productivity making inhabitants even more susceptible to drought and other natural disasters (Li et al.2002). In addition to progressive land degradation due to vulnerable rain- fed, population pressure on land in Rwanda has accelerated poverty so that 46%, on average, of the rural population is impoverished and food insecure earning an average of 90 dollars per capita per year(NISR 2006).

These effects have been exacerbated by the neglect of smallholder agriculture and unreliable weather conditions. At the same time there have been little attempts to harness the water resources of the country. The neglect of agriculture then led to the problem of low productivity, food insecurity and poverty. Therefore in 2007, the government of Rwanda and non-governmental organizations introduced a national food security strategy based on the promotion and implementation of small scale irrigation. The initiative involved the introduction of rainwater harvesting technologies at household level as an alternative intervention to mitigate the effects of the erratic nature of rainfall in the arid and semi-arid parts of Rwanda. The goal of this initiative was to raise agricultural productivity through the promotion of green-revolution type technologies, coupled with natural resources rehabilitation and conservation (Hazell2009). Indeed, water harvesting has been identified as key in achieving national food security in Rwanda (Lagat et al. 2009;MINAGRI 2009).

Rainwater harvesting technologies have been used in many arid and semi-arid parts of the world because of their potential capacity to enhance agriculture productivity and generate income, under the low rainfall conditions. Amha (2006) for example, found that adoption of rainwater harvesting in Ethiopia had a positive effect on value of crop production. Other studies that show a positive impact of rainwater harvesting technologies include; Msangi et al.(2004), Tesfay (2008),Smith et al.(2011), Huhua et al.(2007).

The impact of rainwater harvesting is not however always positive. A study in Northern Ethiopia by Krusema et al.(2006) assessed the impact of small scale water harvesting on household poverty and showed that households with ponds were not significantly better off compared to those without. Mintesnot et al. (2005) attribute their finding to the fact that irrigation technology introduced pests thus negatively affecting crop yields. Pests which were commonly occurring in the rainy season started occurring during the dry season due to the availability of water on the irrigation fields. A study by Lire et al. (2004*)* indicated that small scale irrigation technology introduced in Tigray (Ethiopia) was associated with important health side effects. There were, especially, concerns that new sources of water may have increased the prevalence of water borne diseases such as malaria. These conflicting findings suggest the need for further research on the actual impact of rainwater harvesting ponds. While government of Rwanda and other governments are aggressively promoting the use of these technologies, especially the ponds, there is scarcity of studies that have examined their impacts and factors that condition farmers' adoption of these technologies.

This study aims to provide the evidence on the conditioners of adoption and impact of rainwater harvesting ponds on household's farm income in Rwanda. Besides contributing to understanding of how adoption of rainwater harvesting ponds would change the smallholder farmers' lives, this study will inform policy on how to take appropriate actions towards up scaling of water harvesting technologies.

Theoretical Framework

Theory on adoption of rainwater harvesting technology

In order to assess the factors influencing adoption of ponds, we assume that the adoption of rainwater harvesting technology is a dichotomous choice; the new technology is adopted when the net benefits from using the technology outweigh those of not adopting the technology. We assume that the adoption of rainwater harvesting technology is expected to affect the demand for inputs such as fertilizers, improved seed, as well as yields and incomes. Following Ali and Abdulai (2009) and Okello et al (2012) we assume that the farmer is risk-neutral and minimizes the total cost of production which comprises conventional costs, subject to conventional constraints. The farmer chooses rainwater harvesting technology **I** alongside other inputs to minimize the conventional costs. Algebraically this can be expressed as,

Min C (**WX**) (1)

Subject to a production function specified as:

$Y(\mathbf{X}) = Y(\mathbf{V}, \mathbf{I}\ (\mathbf{T}), \mathbf{L}, \mathbf{K}, \mathbf{z})$ (2)

Where C is the total input cost , **W** is a vector of input prices, **X** is vector of all production inputs, Y is the output produced and sold (as a result of using rainwater harvesting technology), **V** is a vector of conventional variable inputs such as, fertilizer, seed, and pesticides used by the farmer, **I** is irrigation water whose use embodies the use of rainwater harvesting technology **T**, **L** is the total labour requirement including both family and hired labour, **K** and **z** are fixed and quasi-fixed capital inputs and institutional factors, respectively.

The farmer's optimization problem is therefore to choose **I** which minimize the total cost of production subject to a given quantity of output as expressed below. Stated differently, the farmer will decide to adopt rainwater harvesting ponds if doing so minimize the total cost of production subject to a target output. That is;

Subject to:

We write out the lagrangian function for this problem as follows;

and obtain the conditional factor demand for using rainwater harvesting technology.

The solution of the lagrangian function associated with the cost minimization problem yields, among others, I^* which is conditional input demand equation (associated with rainwater harvesting technology) as functions of output Y, input prices W, conventional variable inputs V, fixed factors K and institutional factors z. That is:

$I^* = I^*(W, Y, V, K, z)$. (6)

Equation (6) above also gives the technology adoption function.

Estimation of impact of rainwater harvesting ponds

Following Ali and Abdulai (2009), we model the impact of the adoption of new technology in small scale farming on household income as a linear function of explanatory variables (X_i) and an adoption dummy variable(R_i).The linear regression model for assessing the impact of ponds on income can be specified as;

$$Y = \beta X_i + AR_i + \mu_i \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad (7)$$

Where Y is the mean income of the household, R_i=1 if the technology (rainwater harvesting pond) is adopted and 0 otherwise, μ_i is the error term.

Whether farmers adopt the rainwater harvesting pond technology or not is dependent on the characteristics of farmers and farms, hence the decision of a farmer to adopt is based on each farmer's self-selection instead of random assignment.

Assuming a risk-neutral farmer, the index function to estimate adoption is expressed as

$$R_i(i=)^{\wedge *} \gamma X_i + e_i \qquad \text{...} (8)$$

where R_i* is a latent variable denoting the difference between utility from adopting the technology U_{iA} and the utility from not adopting the technology (U_{iN}). The farmer will adopt the new technology $R_i^* = U_{iA} - U_{iN}$ **>0**. The term γX_i provides an estimate of the difference in utility from adopting the technology (U_{iA}-U_{iN}), using the household and farm-level characteristics, as explanatory variables, while e_i is an error term. In estimating equations (7) and (8), it needs to be noted that the relationship between a new technology and outcome such as income could be interdependent. Thus, technology can help increase output and as such richer households may be better disposed toward the adoption of new technologies. Thus, treatment assignment is not random, with the group of adopters being systematically different, resulting in selection bias problem.

Specifically, selection bias occurs if unobservable factors influence both the error terms of the income equation (μ), and the technology choice equation (ε), thus resulting in correlation of the error terms of the outcome and technology choice specifications. Hence, estimating equation (7) with ordinary least squares will lead to biased estimates. To control for self selection bias, some authors have used the Heckman method while others have used the instrumental variable method. However, due to the restrictive assumption of normality by the Heckman method and the difficulty in finding a suitable instrument, this study employed propensity score matching technique proposed by Rosenbaum and Rubin (1983).This technique matches the two groups so as to create a plausible counterfactual which will then address the problem of selection bias. Specifically, it matches a treated with a control individual that is similar in all observable characteristics except the treatment and computes the difference in outcome variable. That difference is the impact of treatment (i.e. technology adoption).

Empirical methods and Data

Empirical methods

This study uses a logit regression model to examine the drivers of adoption of rainwater harvesting ponds. Specifically, we test three hypotheses namely: that physical, financial assets endowment and group membership do not individually affect the decision to adopt ponds. Following Maddala (1983, 2001), the probability, *p*, that a household adopts rainwater harvesting pond is given by a logit model specified as:

$$P = e^z/1+e^z \qquad (9)$$

Where *z* is a latent variable that takes the value of 1 if the farmer adopted rainwater harvesting pond and 0 otherwise.

Central to the use of logistic regression is the logit transformation of *P* given by *Z*

$$Z = ln\ (P/1\text{-}P) \qquad (10)$$

Where;

$$Z = Z(\boldsymbol{f}, \boldsymbol{z}, \boldsymbol{a}) + \boldsymbol{\varepsilon} \qquad (11)$$

and $\boldsymbol{f}$ is a vector of farmer characteristics, $\boldsymbol{z}$ is a vector of farm level variables, $\boldsymbol{a}$ is a vector of asset specific variables and $\boldsymbol{\varepsilon}$ is the stochastic term assumed to have a logistic distribution. The empirical model estimated contains the following variables (letters in parenthesis indicate related category variables from the conceptual model):

1). Farmer specific variables (*f*) = age, gender ,land ownership, household size

2). Farm specific variables (*z*) = distance to the input market, distance to the agric. extension office and farm size.

3). Asset endowment characteristics (***a***):

a). Physical asset (income, current value of physical assets, access to credit)

b). Human capital (education, experience)

c). Social capital (group membership).

Therefore, the probability of household adoption is estimated using the following implicit functional form:

P(X) = Adopt rainwater pond (age, gender, education level, distance to market, farm size, household size, credit access, distance to the agric extension agent, land ownership, income, current value of assets, farming experience, group member) + e (12)

To address the second objective, we test the null hypothesis that the use of rainwater harvesting ponds has no impact on farm income of the small scale farmers by using the propensity score matching (PSM) procedure. According to Baker (2000) there are 5 steps in PSM. The procedure in PSM starts by obtaining propensity scores (probability of being in a treatment given the observable characteristics), achieved by estimating a binary logit model separate from the above. In the second step matching algorithm is selected based on the data at hand after undertaking matching quality test. Then matching the controls to each treatment using the selected matching algorithms. Matching was done in this study by using Nearest Neighbour Matching (NNM), Radius Matching (RM) and the Kernel Based Matching (KBM). The third step is identifying the common support assumption, which is achieved by visual analysis of the propensity score density distribution. In the fourth stage the treatment effect is estimated based on the matching estimator selected on the common support region. Finally, sensitivity analysis is undertaken to check if the influence of an unmeasured variable on the selection process is so strong to undermine the treatment effect. This is achieved by using the Rosenbaum bounds (rbounds) test.

Data and Sampling procedure

This study uses data collected from 180 farmers during the month of March 2012 through personal interviews conducted by trained enumerators using a pre-tested questionnaire in Kirehe district of Rwanda.Multi-stage sampling procedure was used to select a sample for data collection. The district was purposively selected for the household survey on the basis of the difference in agro-ecology (low land) and was chosen over other districts because unlike the others, it has a considerable number of rainwater harvesting ponds. After selecting the district, the next step was to identify sectors that have rainwater harvesting ponds. From the 12 sectors that constitute Kirehe, 11 sectors were purposively selected since they had a considerable number of both adopters and non adopters of rainwater harvesting ponds. From these sectors, 18 villages were randomly selected and a list of all farmers registered to have adopted ponds was drawn with the help of Kirehe community-based watershed management (KWAMP) project leaders and farmer leaders. A second list of farmers that had not adopted rainwater harvesting ponds was also obtained with the help of local administration (village elders and agricultural extension officers). Simple random sampling was used to select 10 farmers (5farmers with ponds and 5without ponds) from each village. This procedure resulted in 90 farmers who have adopted rainwater harvesting ponds and 90 non-adopters, giving a total sample of 180 farmers.

Table 1 and 2 describes the data collected and provides summary statistics of key variables used in this study and the results of the test of equality of means between adopters and non-adopters. As shown by the t-tests, household with rainwater harvesting ponds differ from their counterparts with respect to average age, initial training, household size, land size, value of purchased inputs, farm income, value of assets, experience in farming and group membership. Below, we investigate these findings further using regression analysis.

Table 1: Definition of Variables used in empirical estimations

Variable	**Variable definition**
Dependent Variables	
Adoption (1=Adopter 0=Non-Adopter)	Whether a farmer has adopted or not
Household input use per acres(Rwf)	Value of input used during 2011 planting season
Household farm income (Rwf)	Income earned from farm source in 2011 planting season
Farmer level variables	
Age in years	Age of the household head
Gender (1=Male 0=Female)	Gender of the household head
Training (1=yes, 0=No)	Initial training of the farmer on RWH technology
Household size(count)	Number of people in the household
Land ownership	Whether farmer owns land
Farm level variables	
Distance to input market(min)	Distance to the nearest input market in walking minutes
Distance to extension office(min)	Distance to agric. extension office in walking minutes

Land size in acres	Total land owned by the household in acres
Asset endowment Variables	
LnAssVal	Natural log of total asset value of the farm in Rwandan francs
Ln farminc	Natural log of farm income during 2011
Lnonfarminc	Natural log of non-farm income during 2011
Credit(1=yes, 0=No)	Farmer access to credit
Education (years)	Educational background of the household head
Experience(years)	Years of experience in farming
Group membership (1=Member 0=Non-member)	Membership to a farmer group

Source: Authors Survey, 2012

Table2: Summary statistics of households with and without pond in Kirehe district, Rwanda.

Variable	**Household with pond (N=90)**		**Household without pond (N=90)**		**t-test of difference in means**	
	Mean	stddev	Mean	stddev	t- stat	p value
Farmer-specific characteristics						
Age (years)	46.71	10.47	42.37	11.50	2.65	0.009***
Gender (1= Male , 0= female)	0.92	0.26	0.87	0.34	1.21	0.228
Receive training(1=yes, 0=No)	0.98	0.14	0.00	0.00	62.57	0.000***
Household size(number)	6.51	2.12	5.33	1.83	3.98	0.000***
Own land(1=yes, 0=No)	0.98	0.14	0.98	0.14	0.00	1.000
Farm-level characteristics						
Distance to extension agent(min)	51.66	48.85	53.36	53.53	-0.22	0.824
Distance to the market (min walk)	64.05	52.74	60.27	47.74	0.50	0.615
Total land size (acres)	5.21	6.70	2.74	3.05	3.18	0.002***

Total value of purchased inputs per acre(Rwf)	46650.23	31829.36	27620.28	30343.70	4.10	0.000***
Asset endowment characteristics						
Ln farm income	12.88	1.93	11.54	3.07	3.49	0.001***
Ln of non-farm income	7.17	6.08	5.83	5.73	1.52	0.130
Ln current value of assets	12.39	1.23	11.10	1.23	6.96	0.000***
Credit(1=yes, 0=No)	0.46	0.50	0.40	0.49	0.75	0.545
Education (years)	4.86	2.30	4.69	2.14	0.50	0.616
Experience (years)	24.10	11.98	21.20	11.43	1.66	0.099*
Group membership(1=yes, 0=No)	0.70	0.04	0.41	0.49	4.05	0.000***

Source: Authors, 2012

Note: Significance of mean difference is at the *10 percent, **5 percent and ***1 percent levels(Note; exchange rate in 2012 was US$ 1 = Rwf 609)

Results and Discussion

Logit regression results of the factors influencing adoption of rainwater ponds

Table3 presents the results of logit regression model estimated to examine the factors influencing adoption of rainwater harvesting ponds. In estimating the model, the variables age and distance to extension agent were dropped since the variables age and farming experience, distance to market and distance to extension agent were found to be highly correlated with $R^2$of 0.713 and $R^2$of 0.568, respectively, indicating that inclusion of all these variables in a regression model will results in a multi-collinearity problem. The likelihood ratio reported below indicate a very low p value=0.000 which implies that the model fits the data well.

Table 3: Logit regression results of the factors influencing adoption of rainwater ponds.

Maximum likelihood estimates			Marginal effects	
Variable	**Coefficient**	**p-value**	**Coefficient**	**p-value**
Farmer-specific characteristics				
Gender	0.199	0.767	0.049	0.765
Household size	0.219**	0.033	0.054 **	0.033
Title deed	-0.456	0.734	-0.112	0.726
Farm-level characteristics				
Distance to market	0.003	0.372	0.008	0.372
Land size	0.071	0.155	0.017	0.155
Asset endowment				
Ln farm income	0.151*	0.083	0.037*	0.083
Ln assets value	0.830***	0.000	0.207 ***	0.000
Credit access	-0.056	0.885	-0.014	0.885
Education	-0.052	0.546	-0.012	0.546
Farming experience	0.016	0.332	0.004	0.332
Group membership	0.646*	0.092	0.160*	0.084
Cons	-13.625	0.000		

Source: Authors 'computation, 2012

*significant at 10% **significant at 5% and *** significant at 1%

Pseudo R2 0.2772

LR $\chi 2$ (P value) 69.18 (0.000)

Hosmer-Lemeshow $\chi 2$ (8) = 3.49Prob> $\chi 2$ = 0.9000

The results show that four factors condition the likelihood of adoption. As hypothesized, household endowment with physical assets significantly affect the decision to adopt rainwater harvesting ponds. Specifically, the result (marginal effect) indicates that an increase in physical assets by 1 unit increases the likelihood of adoption of rainwater harvesting ponds by 20 percent, other things being equal. Thus the null hypothesis that physical assets have no effect on adoption of rainwater harvesting ponds is rejected at 1 percent.

This means that households with higher levels of assets endowment were more likely to adopt rainwater harvesting ponds than their counterparts and suggests that adoption of rainwater harvesting ponds can exclude poorer farmers. The other factors that affect the decision to adopt rainwater harvesting ponds are household size, farm income and group membership.

Results also show that household size is positively related to the farmer's likelihood of adopting rainwater harvesting ponds. The coefficient on household size had the expected positive sign and is statistically significant at 5 percent. This means that households with large family size are more likely to adopt the technology probably because they raise the labour needed to expand production under irrigated system.

The level of household farm income influences the decision to adopt rainwater harvesting ponds positively. The maximum likelihood estimates of the variable *Lnfarminc* is positive and significant (at 10 percent level). A 1 % increase in the farm income increases the likelihood of the household to adopt rainwater harvesting pond by 15.1%, other things being equal. This finding suggests that farmers with financial endowment have higher probability of adopting rainwater harvesting ponds. The finding that households with higher levels of financial capital are more likely to adopt rainwater harvesting ponds than their counterparts further supports the earlier argument that adoption of rainwater harvesting ponds can exclude poor farmers.

Results further show that membership in farmer organizations is also positive and significant at 10 percent, indicating that the probability of adopting rainwater harvesting ponds is affected by the membership to farmer organizations. This means that membership of household heads in farmer organizations have a positive influence on farm household's decision to invest in rainwater harvesting ponds. This finding is in-line with those of previous studies Salasya et al. (1996) and Odendo *et al.* (2010), which indicate that collective action affects adoption of new techniques of farming.

Impact of ponds on household's farm income and household's input use per acre

Results of the logit are shown in Table 4 below.

Table 4: Maximum likelihood estimates of the Logit regression used in estimating the propensity scores

Variable definition Dependent variable = Adoption of rain-water harvesting pond	Coefficient	p-value
Farmer specific variables		
Age	0.135	0.338
Age square	-0.001	0.416
Gender	0.247	0.704
Farming experience	-0.002	0.933
Farm specific variables		
Distance to nearest input market(minute walk)	0.002	0.489
Household size	0.179*	0.100
Asset endowment variables		
Natural log of current value of assets	0.841***	0.000
Credit access	-0.152	0.705
Land size (acres)	0.084*	0.097
Education	-0.027	0.742
Group membership	0.718*	0.057
Constant	-15.36	0.000
No. of observations: 180		
Pseudo R^2 : 0.2695		
p-value : 0.000		
Log Likelihood: -91.147		

Source: Authors, 2012

*significant at 10% **significant at 5% and *** significant at 1%;

The likelihood ratio test of goodness of fit has a p value of 0.000 indicating that the model fits the data well. Furthermore results of the maximum likelihood estimation of the Logit show that household size, group membership and farm size and current assets affect the likelihood of household's adoption of rainwater harvesting ponds. As such the individuals adopting rainwater harvesting ponds differ significantly from the non-adopters with respect to observable characteristics. Therefore, comparing the two groups as they are could have resulted in a selection bias and thus the need to correct for selection bias is in this case justified.

Propensity score matching is one such technique that controls for such bias by reducing imbalances between covariates for both groups and making them comparable. The density distribution of the propensity scores for adopters and non-adopters is shown in the figure below. Visual analysis of the density distribution of the propensity scores in both groups is one of the ways of checking the overlap and the region of common support between the treatment group and the comparison group.

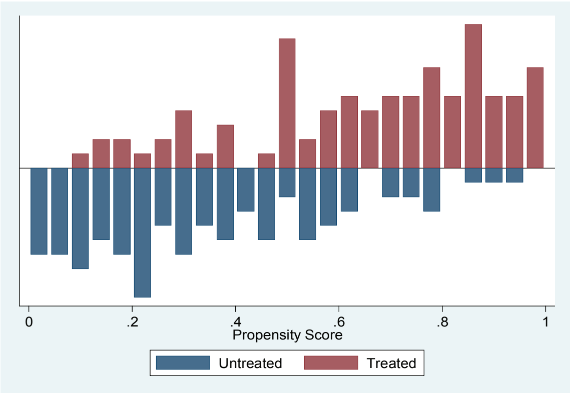

Figure1: *Distribution of the propensity scores on the region of common support.*

Source: Authors, 2012

From the figure above, all the treated and the untreated individuals were within the region of common support indicating that all treated individuals have corresponding untreated individuals.

This shows that the assumption of common support was attained.

Table 5 presents the results of the covariate balancing test performed to test the hypothesis that both groups have the same distribution in covariates x after matching. It presents the covariates 'means', their t-test of differences in means as well as the percentage bias before and after matching. In this case difference in covariates in the two groups has been eliminated hence the matched comparison group can be considered as a plausible counterfactual. Therefore these results were used to evaluate the impact of adoption of ponds on farm income and input use per acre among groups of households having similar observed characteristics.

Table 5: Covariate balancing tests for propensity score.

		Mean			%re-duc-tion	test
Variable	Sample	Treated	Con-trol	%bias	|bias|	p>|t|
Age	Un-matched	46.7	42.3	39.5		**0.009**
	Matched	46.7	46.2	3.8	90.3	0.776
Age squared	Un-matched	2290.4	1925.7	34.4		**0.022**
	Matched	2290.4	2229.4	5.7	83.4	0.672
Farming experience	Un-matched	24.1	21.2	24.8		**0.099**
	Matched	24.1	22.4	14.1	43.1	0.329
Gender	Un-matched	0.9	0.8	18.1		0.227
	Matched	0.9	0.9	-9.9	60.0	0.540
Education	Un-matched	4.8	4.6	7.5		0.616
	Matched	4.8	4.5	14.0	51.8	0.350
Household size	Un-matched	6.5	5.3	59.4		**0.000**
	Matched	6.5	6.1	9.7	83.7	0.535
Access credit	Un-matched	0.4	0.4	11.2		0.454

	Matched	0.4	0.4	10.1	10.0	0.501
Distance to local market	Un-matched	64.0	60.2	7.5		0.615
	Matched	64.0	60.4	6.7	22.4	0.284
Current asset	Un-matched	12.3	11.1	103.8		**0.000**
	Matched	12.3	12.1	18.3	82.4	0.190
Group Membership	Un-matched	0.7	0.4	60.4		**0.000**
	Matched	0.7	0.8	-10.1	86.7	0.490
Farm size	Un-matched	5.2	2.7	47.5		0.321
	Matched	5.2	3.6	30.7	35.5	0.415

Source: Authors, 2012

As shown in Table 5 above, the matched sample means were almost similar for both the treatment and the control which was not the case prior to matching for all the 11 covariates. This means that propensity score matching adequately served the role of reducing imbalances between the covariates for both groups and that of selection bias and that the outcomes between the two groups can thus be compared with the matched covariates.

The second matching statistic employed to assess the quality of matching was the pseudo-R^2 from the logit estimation of the conditional probabilities of adoption. The results in Table 6 indicate that the pseudo-R^2 after matching was lower than before matching for all matching algorithms, as referred (Ali and Abdulai, 2009). This implies that after matching there were no systematic differences in the distribution of covariates between adopters and non-adopters. The p-values of the likelihood ratio tests indicate that the joint significance of the regressors could not be rejected at any level of significance before matching, however after matching the joint significance of the regressors were rejected. This suggests that there was no systematic difference in the distribution of covariates between adopters and non-adopters after matching.

Table 6: Other Covariate Balances Indicators Before and After Matching with NNM, RM and KBM.

Matching algorithm	Mean standard bias before matching	Mean std bias after matching	Pseudo - R^2 unmatched	Pseudo -R^2 matched	P-value Unmatched	P-value matched
Nearest Neighbour Matching	37.6	15.3	0.270	0.079	0.000	0.310
Radius Matching	37.6	17.4	0.270	0.067	0.000	0.119
Kernel Based Matching	37.6	15.4	0.270	0.052	0.000	0.292

Source: Authors, 2012

Together, the results of these tests show that the matching procedure using PSM was able to balance the characteristics of the treated and the matched comparison groups. This implies that the comparison group is a credible counterfactual and also indicates the absence of bias which implies that the computed estimates of the project impact (technology adoption) are valid given the sample.

The results from all matching approaches indicated that adoption of rainwater harvesting ponds have a positive and significant effect on level of household farm income.

Table 7: Impact of adopting pond on household farm income and input use per acre

Matching Algorithm	Outcome Variable	ATT	No. of treated	No. of control	Critical level of Hidden bias (ᴦ)
Nearest Neighbour Matching	Household input use per acre	19814.78*** (2.70)	90	90	2.00-2.05
	Household farm income per acre	90985.96** (2.45)	90	90	1.60-1.65
Radius Matching	Household input use per acre	21147.98*** (3.37)	90	90	2.2-2.25
	Household farm income per acre	87748.69** (2.05)	90	90	1.70-1.75
Kernel Based Matching	Household input use per acre	20141.28*** (3.32)	90	90	2.5-2.55
	Household farm income per acre	89409.45** (2.28)	90	90	1.45-1.50

Source: Authors, 2012

Note: Numbers in parentheses are t-values.

Results of the analysis of the impact of adopting rainwater harvesting ponds using NNM, RM and KBM indicate that the adoption of rainwater harvesting ponds has a positive effect on household farm income per acre. The NNM, RM and KBM causal effects were about Rwf 90985(US$149), Rwf 87748(US$144) and Rwf 89409(US$147) respectively. This implies that average household farm incomes per acre of adopters of rainwater harvesting ponds were higher than that of non-adopters.

In order to assess the pathway by which adoption of rainwater harvesting ponds affected household income, we examined the effect of adopting rainwater harvesting ponds on input use as well. Results from NNM, RM and KBM show that the adoption of rainwater harvesting ponds increased household input use per acre by between Rwf 19814 (US$ 32) and Rwf 21147(US$ 35). This suggested that input use is higher among adopters of rainwater harvesting ponds than the non-adopters. As expected adopting rainwater harvesting ponds increases use of purchased inputs.

We performed sensitivity tests on the results of this study. The purpose of the sensitivity analysis is to assess whether inferences about adoption effects may be altered by factors not observed in the dataset (unobserved variables).Rosenbaum bounds (rbounds) test which tests the null hypothesis of no effect on the treatment effect for different values of unobserved selection bias was used. This test computes the gamma level, which is defined as the odds ratio of differential treatment assignment due to an unobserved covariate.

From Table 7 above, in all the three matching algorithms the lowest critical value of sensitivity analysis was 1.45–1.50, whereas the largest critical value was 2.5-2.55.For a gamma level of 1.45–1.50 for the adoption of rainwater harvesting ponds on farm income, it implies that the unobserved variable would have to increase the odds ratio by 45 to 50 percent before it would bias the estimated impact, i.e. if the individuals that had the same characteristics (X vector) were to differ in their odds ratio of adoption of rainwater harvesting ponds by a factor of 45 to 50 percent then the significance of the estimated impact of adoption on household farm income would be questionable. We therefore concluded that even large amounts of unobserved heterogeneity would not alter the inference about the estimated effects of use of rainwater harvesting ponds on level of household input use per acre and household farm income. Hence we conclude that adoption of rainwater harvesting ponds affect household farm income.

Summary, conclusions and policy implications

The study assessed the drivers of adoption of rainwater harvesting ponds and effect of adoption of ponds on household input use and farm income. It found that the major factors driving the adoption of rainwater harvesting ponds are household size, membership to a farmer organization, farm income and endowment of physical assets. It further concludes that the use of rainwater harvesting ponds has a positive impact on household farm income per acre by about Rwf 90,985 (US$ 149). The positive impact of the adoption of rainwater harvesting ponds on household farm income per acre occurs via increased use of inputs. Indeed, as results demonstrate, the adoption of rainwater harvesting ponds increase input use per acre by about Rwf 21,147 (US$ 35).

The implication of these findings is that adoption of rainwater harvesting ponds presents a pathway for reducing rural poverty. Therefore policies that target promotion of membership in farmer organizations should be pursued alongside the promotion of rainwater harvesting ponds. There is also need to develop the input (fertilizer, manure, improved seed and pesticide) markets to make such inputs more easily accessible to farmers. In addition there is need for policies and strategies that target the inclusion of poor farmers in adoption of rainwater harvesting ponds. Finally, research and development interventions should target ways of reducing the cost of adopting rainwater harvesting technology in order to include the poorer farmers.

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