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Adoption and Impact of Rainwater Harvesting Technology in Nepal

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ABSTRACT

The rainwater harvesting (RWH) technology has been introduced to upland farmers in Nepal who have been practicing rain-fed subsistence agriculture. Using cross-sectional household level data from 282 farmers in four districts of Makwanpur, Palpa, Gulmi and Syangja, probit and treatment-effects models were used to identify factors that influence the adoption of RWH and its impact on farm income. The adoption of rain water harvesting was mostly driven by trainings that farmers received while controlling for age, poverty status and off-farm income. The adoption of RWH technology more than doubles household agricultural and livestock income. Instrumental variable approach was used to check the robustness of the findings. Adopters benefited from an increased supply of irrigation water, which allows them to diversify their crops from cereal production to high-value crops during dry season. Given the many weather-related uncertainties faced by rainfed farmers in Nepal, rain water harvesting is potentially a very useful climate adaptation strategy. These results were robust to alternative model specification and estimation method.

Keywords: Rainwater harvesting, Rainfed agriculture, Technology adoption, Treatment-effects, Nepal.

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INTRODUCTION

Climate change will affect water resources, with implications for agricultural systems and food security (Bartlett et al 2010). Adverse impacts will be especially critical in a country such as Nepal, where about 66% of the population is directly dependent on subsistence and mostly rain-fed agriculture for livelihoods. This is particularly worrying because water is the major limiting resource for crop production in rainfed agricultural systems (APN 2004, Wani et al 2009). Thus, it is important to try and understand how water can be better conserved and more effectively used for agriculture. In this paper, we address this issue in the context of a specific water conservation technology, i.e., rainwater harvesting (RWH), which is being increasingly used in Nepal in recent year.

Weather dependent rainfed agricultural land accounts for 65% of the total cultivable land area in Nepal. Since only 24% of the arable land is irrigated, crop productivity is significantly low in Nepal in comparison with the rest of South Asia, leading the country to rely heavily on food imports from India (Bartlett et al 2010).Agriculture consumes around 96% of all water withdrawn in the country (CIA 2010) and contributes about 34% to the GDP (World Bank 2012).

In Nepal, more than 80% of precipitation occurs a short monsoon season (June to September). This monsoon rainfall is characteristically heavy, leading to flooding, landslides and loss of top soil (Malla 2008). These occurrences contribute to crop failure and increased food and livelihood insecurity (Lohani 2007, Malla 2008, Kohler et al 2010, Gentle and Maraseni 2012). In the absence of year-round irrigation facility, short window of rainy season makes seasonal farming impossible, especially for crops that have a reasonable market value such as rice, maize, wheat and vegetables (Gurung and Bhandari 2009). People in the hilly areas of Nepal are subject to even more livelihood risks as water sources are increasingly scarce and located beyond a reasonable distance, usually below the farmland where gravity irrigation is not possible.

In this context, RWH technologies have become increasingly important as adaptation strategies to manage water problems posed by climate change and rainfall variability (Getnet and MacAlister 2012, Mutekwa and Kusangaya 2006, Hatibu et al 2006, Moges et al 2011). RWH technology generally involves harvesting rainwater and diverting it to reservoirs for the purpose of coping with rainfall variation and drought. The aim is to enhance soil infiltration at the site and improving rainfed cultivation through the use of stored water. There are two commonly deployed RWH practices: surface rainwater harvesting and rooftop rainwater harvesting, both are equally important. The focus of this study is the individually-managed plastic or cemented RWH ponds, which were recently introduced in the hilly regions of Nepal.[1]

The Government of Nepal is promoting non-conventional irrigation systems like RWH, drip irrigation and treadle pumps as part of its 2013 Irrigation Policy (MOI 2014). However, to date, only about 5% farmers have adopted RWH for crop production, at least in the study area. Little is known regarding why certain farmers have adopted this technology while others have not. Thus, if RWH technologies are to be scaled up in Nepal, it is important to understand farmer's adoption decisions. Consequently, in this study, two inter-related questions were examined: 1) what are the factors that determine the adoption of RWH technology by rural farmers? and 2) what is the impact of RWH technology on farm income?

MATERIALS AND METHODS

Study Area and Sampling

This study conducted in four mid-hill districts of Nepal, namely, Makwanpur, Palpa, Gulmi and Syangja. These four districts have been chosen purposively for two main reasons: firstly, they have recorded the highest rates[2] of individually-managed RWH technology adoption and, secondly, they allow us to capture variation in rainfall and elevation across the hilly districts of Nepal. Rainfed agriculture is predominantly practiced in these areas and is associated with the cultivation of major staple crops such as maize, wheat, rice, millet and vegetables.

The farm household survey was conducted through a structured survey interview of 282 farm households comprising 141 RWH adopters and 141 non-adopters in 2012 and followed up survey was done in 2022. Study used multistage sampling technique where four districts from were selected purposively. Villages from each district were selected based on the RWH technology adoption rates. Secondly, farmers were stratified in each village into two groups, namely, adopters and non-adopters. In each sampled village, there were fewer numbers of RWH technology adopters than non-adopters.[3]. Ten to fifteen households[4] from each village among the population of individually-managed RWH adopters and non-adopters were sampled. three community-level Focus Group Discussions (FGDs) in each district were conducted. Around 5 to 10 RWH adopters/non-adopters participated in each FGD (including farmers from different castes, genders and economic backgrounds). The FGDs provided qualitative information for understanding farmers' perspective on adopting or not adopting the RWH technology and this information were considered while designing the survey instrument.

Empirical Methods and Variables

In order to better understand RWH technology adoption and to assess its impact on farm household income, we specify and estimate a set of econometric models. Household income and adoption of RWH technology may affect each other, where household with higher income may adopt RWH technology and adoption of RWH technology may also increase farm income. The problem can be resolved technically using either a treatment-effects model as in Maddala (1983) or an instrumental variable (IV) approach, instrumenting an endogenous RWH adoption dummy, as in Angrist (2000). It was estimated the equations describing farmers' adoption decision and farm income simultaneously using a treatment-effects model to control for self-selection (Heckman

[1] Harvesting rainwater for domestic animals is an old-age tradition in the hills of Nepal but rainwater harvesting for agriculture is relatively a new phenomenon.

[2]The National Population and Housing Census Report (2011), District Profile (2011) and the District Agriculture Development Office Report (2011) were used to gather secondary information, including information on the RWH adopters' list, household population size, and the occupational diversity of the households living in the selected villages in order to develop the sampling frame. The list of villages and adopters were obtained from the 2011 Census of Nepal.

[3] 20 to 120 RWH adopters and 100 to 410 non-adopters in each sample village were found.

[4]10 to 20 households were randomly selected from each village where 5-10 were RWH adopting HHs (Treatment HHs) and 5-7 were RWH non-adopters/participants (Control HHs).

1978, Heckman 1979, Heckman and Navarro-Lozano 2003). We also use an IV approach for checking robustness of the estimates obtained from treatment-effect models.

Modeling of adoption of RWH technology

The decision to adopt an available agricultural technology depends on a variety of factors including farm households' asset bundles and socio-economic characteristics, characteristics of the technology, perception on the need of new technology, and the risk-bearing capacity of the household (Mendola 2005, He et al 2005, Namara et al 2007, Adeoti 2009, Abdulai et al 2011, Getnet and MacAlister 2012). An 'asset bundle' comprises physical, natural, human, social, institutional, technical and financial assets.

In this study, it was assumed that farmers are risk-neutral and that their adoption decision is based on the comparison of their expected utility with and without the adoption of the RWH technology:

$$d_i^* \equiv E\left(\Pi_i^1\right) - E\left(\Pi_i^0\right) > 0, \quad (1)$$

where the latent variable, d_i^*, is not observed and Π_i^1 and Π_i^0 are the utilities with and without the adoption of the RWH technology respectively. The expected net utility from adopting the RWH technology can be modeled as follows: $d_i^* = \mathbf{X}_i'\gamma + \varepsilon_i$, where the vector $\mathbf{X}_i$ includes characteristics of the farmer and the farm's environment. The decision model for farmer *i* is thus written as

$$d_i^* = \mathbf{X}_i'\gamma + \varepsilon_i \geq 0. \quad (2)$$

We use the probability that farmer *i* adopts the RWH technology using the following Probit model:

$$d_i = F\left(\mathbf{X}_i'\gamma\right) + \nu_i, \quad (3a)$$

$$RWH\ Technology_i \quad (Yes = 1) = \alpha_0 + \alpha_1.Age_i + \alpha_2.Gender_i + \alpha_3.Education_i + \alpha_4.Economic\_HH_i$$
$$\alpha_5.Shareupland_i + \alpha_6.Training_i + \alpha_7.\ln OfffarmIncome + \alpha_8.Poor_i + \lambda_d + \omega_i \quad (3b)$$

Where, d_i equals 1 if the expected net utility d_i^* is positive and 0 otherwise. Function *F* is the cumulative distribution of the ε_i error term, assumed to be standard normal.

Based on the review of relevant literature, the following explanatory variables were used in the adoption model (equation 3b): age, gender and education of household head, number of economically-active members in household, share of upland plots in total cultivated land, agriculture and livestock production-related training received by the household, annual household off-farm income, poverty status[5], and district fixed effects (see Table 1 for a detailed description of these variables).

Income model

The following model was used to estimate the impact of the RWH technology on annual household income from the agriculture and livestock sectors:

$$\ln INC_i = \beta_0 + \beta_1.LSU_i + \beta_2.\ln Spade_i + \beta_3.\ln Totalland_i + \beta_4.\ln Shareupland_i$$
$$\beta_5.RWH\ Technology_i \quad + \lambda_d + \omega_i \quad (4)$$

Where, $\ln INC_i$ is the log of annual household income from agriculture and livestock sectors[6] (measured in Nepalese rupees), *LSU* is Livestock Standard Unit (LSU), *lnSpade* is the number of spades at home (in natural log), *lnTotalland* is the total cultivated land (*ropani*[7]; in natural log), *lnShareupland* is the share of upland in total cultivated land (percentage; in natural log), *RWH Technology* refers to the adoption of the RWH pond (see Table1 for more details on these variables), and λ_d refers to district fixed effects.

RESULTS AND DISCUSSION

The district fixed effect was used to account for the unobservable variables at the district level that may affect the adoption as well as household income. It assumed that the RWH technology adoption depends on age, gender and education of the household head, percentage share of upland plots in total cultivated land, agriculture

[5] Poverty status was based on household income per capita per day.

[6] The income variable used as the dependent variable in the main model included agricultural and livestock income, but did not include off-farm income.

[7] 1 *ropani* = 0.05 hectare (19.67 *ropani*= 1 hectare)

and livestock production-related training received by the household whereas age of the household head, annual household off-farm income and poverty status of the household are assumed negatively determined on RWH adoption. District fixed effects was used to capture topographic features in the study area.

Therefore, nine explanatory variables were used to explain the adoption of RWH technology: *Age*, *Gender* and *Education (*of the household head), *EconomicHH* (aged 15 to 60), *Shareupland* (percent of upland in total cultivated land), *Training (*received on agriculture and livestock production, 1 if yes, 0 otherwise), *lnOfffarmIncome* (annual off-farm income (NRs.) in natural log), and *Poor* (a dummy variable to indicate if the household is poor).

Table 1. Description of variables

Variable name	Description of variable	Obs.	Mean	Std. dev.
RWH Technology	RWH Technology adoption (1 if adoption, 0-otherwise)	282	0.50	0.50
Age	Age of household head in years	282	50.20	13.61
Gender	Gender of the household head (1 if male, 0-otherwise)	282	0.74	0.43
Education	Education of household head (years of schooling)	282	2.00	1.86
EconomicHH	Total household members aged 15 to 60 (economically active)	282	4.08	2.02
lnTotalland	Total cultivated land in *ropani* (in natural log)	282	1.76	1.20
Shareupland	Upland in total cultivated land (percentage)	282	79.50	30.86
Training	Training received on agriculture and livestock production (1 if yes, 0 otherwise)	282	0.46	0.49
lnOfffarmIncome	Annual off-farm income (NRs; in natural log)	282	3.70	5.26
lnSpade	Number of spades (in natural log)	282	1.03	2.00
Gulmi	Survey district (if Gulmi-1, 0-otherwise)	282	0.14	0.34
Syangja	Survey district (if Syangja-1, 0-otherwise)	282	0.15	0.35
Palpa	Survey district (if Palpa-1, 0-otherwise)	282	0.28	0.28
lnFarmIncome	Annual household income from agriculture and livestock (NRs; in natural log)	282	10.79	1.03
Poor	Household is poor[8] (if poor-1, 0-otherwise)	282	0.39	0.49
LSU	Livestock standard units (cattle equivalent in number)	282	3.10	2.39

Socio-demographic and economic characteristics

Table 2 presents the socio-demographic and economic characteristics of the sampled farmers. The average age of the household head was approximately 50 years. Though RWH adopters were on average younger than non-adopters, the difference (between the two means) was not statistically significant. Approximately 74% of the household heads were male with average education of 2 years of schooling. The level of education was higher for adopters than for the non-adopters. Among other variables, the total number of spades in the house, the training received with regard to agriculture and livestock production and the membership of the household head in any group, organization or cooperative were found to be greater among RWH adopters than among non-adopters. There was a greater proportion of higher caste households and those with knowledge of climate change among the RWH adopters than among the non-adopters. The percentage of people below poverty line was lower for adopters (34%) than for non-adopters (45%). This indicates that there was a negative association between RWH Technology adoption and households' poverty. The difference between the sample means in the adopter and non-adopter groups was not statistically significant for the following variables: the livestock standard unit, the availability of extension services at the farm, access to credit, total cultivated land, and percent of upland in total cultivated land. The latter indicates that the two groups of farmers were mostly comparable including landholding size.

[8] A household is considered poor if its income is lower than US$ 1.25/person/day.

Table 2. Socio-demographic characteristics of RWH adopters and non-adopters

Particular	Full Sample (n=282)	RWH Adopters (n=141)	Non-adopters (n=141)	Mean Difference (t-test)
Age of household head (in years)	50.21	48.91	51.50	-2.59
Gender of the household head (if male=1)	0.74	0.81	0.67	0.13***
Years of schooling	4.51	5.31	3.69	1.62***
Caste (if higher caste =1)[9]	0.48	0.53	0.43	0.099*
Family size	6.48	6.58	6.39	0.19
Economically active household members (15 to 60 years old)	4.08	4.22	3.93	0.29
Upland cultivated (in *ropani*)	6.47	7.03	5.91	1.12
Lowland cultivated (in *ropani*)	1.94	1.89	1.99	0.10
Total cultivated land (in *ropani*)	8.41	8.93	7.91	1.29
Percent shared by upland in total land	79.5	80.2	78.7	0.41
Livestock standard unit (LSU)[10]	3.13	3.34	2.93	0.41
Number of spades (type of physical asset)	4.7	5.2	4.3	2.88***
Extension service (if yes =1)	0.43	0.46	0.40	0.06
Agriculture and livestock production related training received (if yes=1)	0.46	0.67	0.24	0.43***
Access to credit (if yes=1)	0.77	0.81	0.74	0.08
Membership in any group, cooperative and/or organization (if yes=1)	0.63	0.72	0.55	0.16***
Knowledge of Climate Change (if yes=1)	0.49	0.54	0.43	0.11*
Poor (if yes=1)	0.39	0.34	0.45	0.11*

Notes: Figures in parentheses are standard deviation. ***Significant at 1% level, *Significant at 10% level.

Approximately 27% of the respondents were grown cauliflower and cabbage. The proportion of farmers growing cauliflower and cabbage was higher among the RWH adopters (39%) than among the non-adopters (22%). The same pattern was discernible for tomatoes, which were grown more frequently by adopters (55%) than by non-adopters (27%) as well as for other vegetable such as bean, pea, broadleaf mustard, and guard. Cereal production was more common among the non-adopters than among the adopters. We thus noticed that most RWH adopters were growing a high-value crop (i.e., vegetable) and that they had diversified their cropping pattern towards vegetables from cereals in contrast to the non-adopters. Figure 1 shows the distribution of different types of vegetables and cereals produced by the RWH adopters and non-adopters.

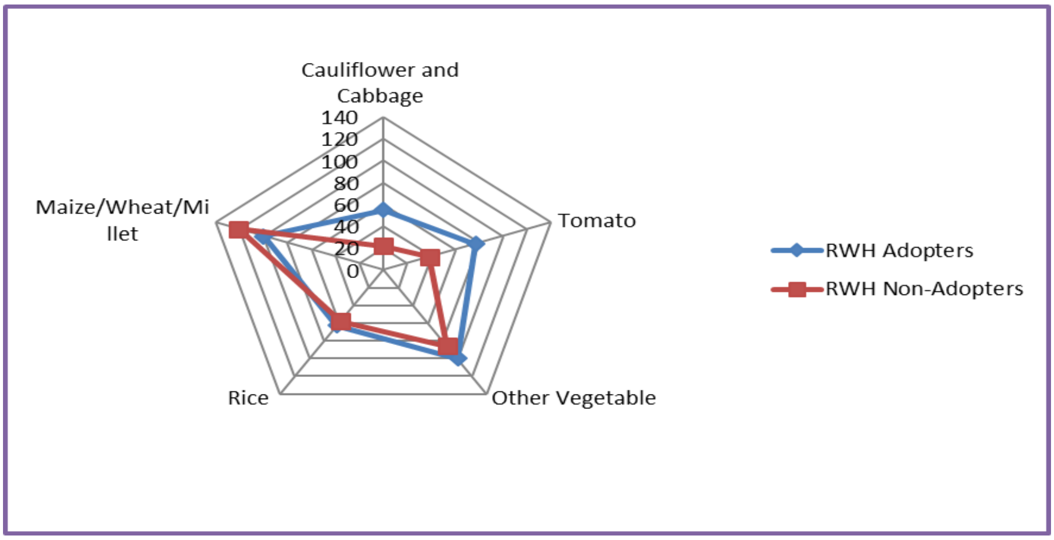

Figure 1. Number of vegetable and cereal crop producers among RWH adopters and non-adopters

Table 3 presents the major crops produced and the revenue from the marketed crops in both the lowland and the

[9] Brahmin, Chettri and Takuri are the higher castes in Nepal.

[10] LSU is Livestock Standard Unit (based on cattle equivalent: 1 cow/cattle= 10 goats/lambs= 4 pigs and = 143 chicken/ducks)

upland during different cropping seasons. The production of cereal crops (mainly, rice, maize, wheat) in upland and lowland areas is not statistically significant. With regard to farm revenue from different crops, revenue from tomato and other vegetables is significantly higher among the RWH adopters.

Table 3. Crops production and revenue of RWH adopters and non-adopters

Particular	Full Sample (n=282)	RWH Adopters (n=141)	Non-adopters (n=141)	Mean Difference (t-test)
Crop production (in quintal):				
Cauliflower/Cabbage	20.08	22.05	14.69	7.35
	(5.08)	(6.41)	(7.43)	
Tomato	50.39	69.82	11.04	58.77
	(26.82)	(39.95)	(2.21)	
Other vegetable	8.33	9.76	6.66	3.09*
	(0.89)	(1.32)	(1.17)	
Rice	19.93	9.78	22.61	-12.82
	(6.75)	(1.94)	(13.95)	
Wheat/Maize	17.36	28.11	8.47	19.63
	(9.04)	(19.93)	(1.22)	
Crops based HH revenue (in NRs.) from:				
Cauliflower/Cabbage	36284	42559	19252	23306
	(7682)	(9932)	(8562)	
Tomato	49179	59175	28945	30220***
	(5629)	(7557)	(6423)	
Other vegetable	19711	22647	16297	6350*
	(1877)	(2833)	(2337)	
Rice	23712	26379	20723	5656
	(2669)	(4546)	(2457)	
Maize/Wheat	18373	19151	17729	1421
	(2109)	(2533)	(3242)	

Notes: Figures in parentheses are standard deviation. ***Significant at 1% level, *Significant at 10% level.

Income from vegetables and fruits, and from agriculture and livestock sectors as well as total annual household income were found to be significantly higher among RWH adopters than non-adopters. However, income from off-farm activities was significantly higher for non-adopters. The annual income from the agriculture and livestock sectors for RWH adopters was NRs. 104,969 while it was just NRs. 53,876 for non-adopters. The RWH technology adopters thus appeared to benefit from an increased supply of irrigation water which allowed them to diversify their cropping system from cereal crops to high-value vegetable crops and livestock (Table 4).

Table 4. Annual household income from different sectors among RWH adopters and non-adopters (in NRs.)

Particular	Full Sample (n=282)	RWH Adopters (n=141)	Non-adopters (n=141)	Mean Difference (t-test)
Cereal crops	23671	23796	23546	250
	(2050)	(2697)	(3111)	
Vegetable and fruit	44148	67446	20850	46595***
	(4663)	(8414)	(2960)	
Livestock	11603	13726	9480	4246*
	(1322)	(2247)	(1379)	
Employment /services	40604	38082	43127	-5045
	(6532)	(9313)	(9191)	
Off-farm	34881	26134	43627	-17492**
	(4311)	(5201)	(6815)	
Foreign employment	40730	47368	34092	13276
	(6899)	(12313)	(6232)	
Agriculture and livestock (cereal + vegetable +	79423	104969	53876	51092***
livestock)	(5739)	(9988)	(4812)	
Total annual household income	195640	216555	174724	41831*
	(11201)	(17713)	(13551)	

Figures in parentheses are standard deviation. ***Significant at 1% level, **Significant at 5% level, *Significant at 10% level.

Determination of farm income and farmers' decision to adopt RWH technology

Six different models were estimated to identify the impact of RWH adoption on farm income: three treatment-effects models (Table 5), two instrumental variable (IV) models, and one OLS model as a benchmark. The first treatment-effects model was the most basic model. Poor and off-farm income were included in second model whereas district fixed effects were included in third model. In case of IV approach, model 2 was basic model.

Table 5. Determinants of household income and RWH Technology adoption (Maximum Likelihood Estimates): Treatment-effects Models

Variable[11]	Model 1	Marginal Effect (dy/dx)	Model 2	Marginal Effect (dy/dx)	Model 3	Marginal Effect (dy/dx)
lnFarmIncome:	Coefficient		Coefficient		Coefficient	
LSU	0.046*		0.049**		0.053**	
	(0.025)		(0.024)		(0.024)	
lnSpade	0.010		0.009		0.009	
	(0.022)		(0.023)		(0.023)	
lnTotalland	0.592***		0.583***		0.543***	
	(0.078)		(0.076)		(0.068)	
lnShareupland	-0.030		-0.031		-0.018	
	(0.023)		(0.022)		(0.023)	
RWH Technology	1.111***		1.380***		1.310***	
	(0.190)		(0.199)		(0.212)	
Constant	9.303***		9.259***		9.379***	
	(0.190)		(0.171)		(0.169)	
RWH Technology:						
Age	-0.014**	-0.003**	-0.016**	-0.004**	-0.017***	-0.004**
	(0.007)		(0.006)		(0.007)	
Gender	0.506**	0.117***	0.705***	0.155***	0.705***	0.154***
	(0.210)		(0.187)		(0.191)	
Education	-0.005	-0.006	-0.053	-0.013	-0.059	-0.015
	(0.042)		(0.037)		(0.041)	
EconomicHH	0.062	0.015	0.053	0.013	0.065	0.016
	(0.040)		(0.043)		(0.043)	
Shareupland	0.004*	0.001*	0.004*	0.001*	0.004	0.001
	(0.003)		(0.003)		(0.003)	
Training	1.103***	0.326***	0.950***	0.274***	0.987***	0.285***
	(0.174)		(0.178)		(0.200)	
lnOfffarmIncome			-0.045***	-0.011***	-0.048***	-0.012***
			(0.015)		(0.016)	
Poor			-0.895***	-0.206 ***	-0.808***	-0.187***
			(0.186)		(0.218)	
Constant	-1.486***		-0.822*		-0.808***	
	(0.4419)		(0.432)		(0.218)	
DFE[12]	No		No		Yes	
/athrho	-0.497***		-0.854***		-0.819***	
/lnsigma	-0.196***		-0.154**		-0.189***	
Rho	-0.460		-0.693		-0.674	
Sigma	0.821		0.856		0.827	
lambda	-0.378		-0.594		-0.558	
Treatment-effects Model-MLE	Wald test of indep. eqns. (rho = 0): chi2(1) =12.34*** Prob> chi2 = 0.0004		Wald test of indep. eqns.(rho = 0): chi2(1) = 28.69*** Prob> chi2 = 0.0000		Wald test of indep. eqns.(rho = 0): chi2(1) =22.08*** Prob> chi2 = 0.0000	

Source: Own calculations *** Significant at 1% level, **Significant at 5% level, *Significant at 10% level. dy/dx is probability (margins) after mfx.

[11]Variables were used that describe the characteristics of the farmer/farm at the time the adoption decision was made. Some characteristics have changed after adoption of RWH pond (like agricultural income, physical assets, and livestock units) and were not included in the model to avoid any endogeneity problems.

[12] District fixed-effects (DFE): Gulmi, Syangja, Palpa (Makwanpur-omitted district)

The district fixed effects were included in third model. The IV and treatment-effects models produced consistent results. The OLS model underestimated the effect of RWH adoption on farm income (45.8%) while the treatment-effects models and IV models indicated that RWH adoption results into 111% to 138% increase in an average household's farm income.

Results indicated that the adoption of RWH technology (*RWH Technology*) significantly increases household income from agriculture and livestock. RWH technology adopting farmers have earned about 131% more annual household income from the agriculture and livestock sectors than the non-adopting farmers in the study area. The livestock holding (*LSU*) and the total cultivated land (*lnTotalland*) also contributed positively to household income.

The most important factor affecting farmers' adoption decision to adopt RWH technology was agriculture and livestock training (*Training*). The age of the household head (*Age*), annual household income from off-farm activities (*lnOfffarmIncome*) and poverty status (*Poor*) had have significant but negative impacts on RWH adoption whereas the training received by farmer and the gender of the household head (i.e., being a male) had significantly positive impacts on the RWH adoption decision. However, other variables like the economically active members in the household (*EconomicHH*), the percent shared by upland in total cultivated land (*Shareupland*), and education of the household head (*Education*) had no impact on the adoption decision.
All else equal, if a farmer receives agriculture and livestock production related training, the RWH technology adoption decision will increase by 28.5%. The training provides knowledge and skill to farmers to adopt innovative technology at the farm. Off-farm income too has a significant and negative impact on the RWH adoption decision. Figure 2 illustrates household farm income by training received and RWH adoption.

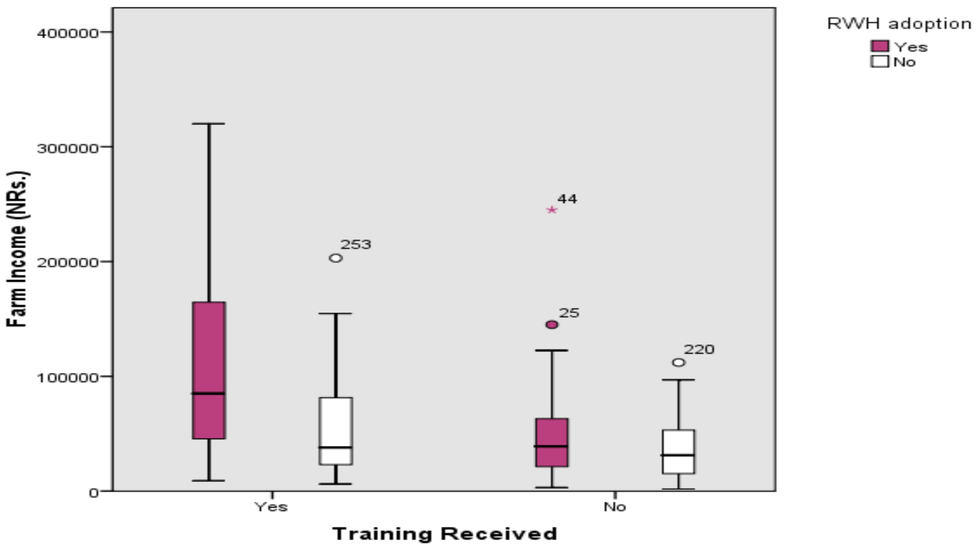

Figure 2. Box plot of farm income by training received and RWH technology adoption

CONCLUSIONS

Findings revealed that adoption of RWH increases annual household income from the agriculture and livestock sectors by over 130%. The technology allows the farmers to diversify their cropping system from cereal crops to high-value vegetables. Although RWH is profitable in rainfed agriculture systems, a majority of farmers seem reluctant to adopt this technology. This is because of lack of technical knowledge, large start-up costs and lack of labor in the villages due to out-migration. Furthermore, without diversifying farm production, this technology is less beneficial. Thus, risk-averse farmers may be less willing to adopt RWH.
This study suggested that at least some of the constraints to adoption can be reduced by providing relevant trainings to the farmers. If a farmer receives farm management training from agricultural extension services, the probability of RWH technology adoption increases by approximately 29%. Thus, policy makers and extension services need to play a more proactive role in promoting RWH technology in the rainfed hilly regions of Nepal by providing credits or subsidy and appropriate trainings to the potential adopters.

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AUTHOR CONTRIBUTION

Dr. Rishi Ram Kattel: Idea generated, Research designed and surveyed, Analyzed and interpreted the data and models and prepared manuscript. Overall whole responsibility.

CONFLICT OF INTEREST

The author declares no conflict of interests or personal relationships that could have appeared to influence the work reported in this paper.

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