Poverty Impacts of Agricultural Water Management Technologies in Ethiopia

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Abstract
Farmers in rural Ethiopia live in a climate related shock-prone environment. The major source of climate shock is the persistent variation in the amount and distribution of rainfall. The dependence on unreliable rainfall increases farmers' vulnerability to shocks while also constraining farmers' decisions to use yield-enhancing modern inputs exacerbating household's vulnerability to poverty and food insecurity. As a response, the government of Ethiopia has embarked on massive investment in low cost agricultural water management technologies (AWMTs). Despite these huge investments, their impact remains hardly understood.

The main focus of this paper was to explore whether access to selected AWMTs, such as deep and shallow wells, ponds, river diversions and small dams, has led to significant reduction in poverty, and if they did so to identify which technologies have higher impacts. In measuring impact we followed different approaches: mean separation tests, propensity score matching and poverty analysis. The study used a unique dataset from a representative sample of 1517 households from 29 Peasant Associations (Kebeles) in four regions of Ethiopia. Findings indicated that the estimated average treatment effect on per capita income was significant and amounted to USD 82. Moreover, there was 22% less poverty among users of AWMTs compared to non-users. The poverty impact of AWMT was also found to differ by technology type. Accordingly, deep wells, river diversions and micro dams have led to 50, 32 and 25 percent reduction in poverty levels compared to the reference, i.e. rain fed system. Finally, our study identified the most important determinants of poverty on the basis of which we made policy recommendations: i) build assets (AWMT, livestock, etc); ii) human resource development; and iii) improve the functioning of labor markets and access to these (input or output) markets for enhanced impact of AWMT on poverty.

Key words: water management, income, consumption expenditure, matching, poverty analysis, Ethiopia

1. Introduction

Farmers in rural Ethiopia live in climate related risk-prone environment. The major source of climate risk is the persistent fluctuation in the amount and distribution of rainfall (Awulachew, 2006; Namara et al., 2006). The dependence on highly variable rainfall increases farmers' vulnerability to shocks while also constraining farmers' to use

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yield-enhancing modern inputs. This exacerbates household's vulnerability to poverty. Poverty in Ethiopia has, in fact, mainly rural dimension. Small-scale farmers are the largest group of poor people in Ethiopia (MoFED, 2006). As a response, the government of Ethiopia has embarked on massive investment in low cost Agricultural water management technologies (AWMTs). Lately the focus has been on development of small-scale micro water harvesting schemes. This wide range of technologies collectively referred to as "smallholder water and land management systems," attempts to create opportunities for the poor and small landholders in accessing water, rain or ground water, which in turn leads to increased production and income. These technologies are reported to be particularly suited to small, poor and even landless households as the costs self-select the poor and have a strong land and water-augmentation effects (Hussain et al. 2001).

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In this line, thousands of shallow wells and dozens of deep wells have been developed since 2002/2003. In Amhara and Tigray Regional states alone a total of approximately 70,000 ponds and tanks were constructed in one fiscal year (Rämi, 2003). There are currently an estimated 56,032 ha of modern small scale irrigation schemes in Ethiopia, comprising micro dams and river diversions (Awulachew et al. 2007) and larger areas under traditional irrigation. The development of these systems has required huge financial input from the government, whose food security budget has increased from year to year, a major chunk of which is used to promote different types of small scale water and land management systems (FDRE, 2004). Despite these huge investments, their impact remains hardly understood, save the anecdotal evidences gathered here and there (Rämi, 2003).

The Comprehensive Assessment of Water Management in Agriculture (IWMI, 2007) states that "improving access to water and productivity in its use can contribute to greater food security, nutrition, health status, income and resilience in income and consumption patterns. In turn, this can contribute to other improvements in financial, human, physical and social capital simultaneously alleviating multiple dimensions of poverty" (P.149). FAO (2008) also argued that well-targeted, local interventions in water can contribute to rapid improvements in livelihoods of the rural poor in SSA and help attain the Millennium Development Goals of eradicating extreme poverty and hunger. In fact, FAO (2008) identified better management of soil moisture and investment in water harvesting and small storage as two of the 6 categories of promising interventions in view of their poverty-reduction potential.

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While evidence on the impact of irrigation on poverty from Asia, be it from large and small systems, is plenty (Hussain, et. al.2001; Hussain, et. al.2006; Hussain, 2005; Hussain, 2007; Huang, et al., 2006; Namara, et al., 2007b) and the research findings consistently indicate that irrigation development alleviates poverty in rural areas of developing countries (Hussain and Hanjra, 2003). Hussain and Hanjra (2004) exploring the linkages between irrigation and poverty reported that the linkages are both direct and indirect. Direct linkages operate via localized and household-level effects, and indirect linkages operate via aggregate or subnational and national level impacts. In general, Hussain and Hanjra (2004), reported that irrigation is productivity enhancing, growth promoting, and poverty reducing. The poverty impact of AWMTs in Asia is also viewed in the same positive light. Hussain et. al. (2001) reported that there has been an upsurge in the adoption of irrigation technologies for smallholders such as low-cost pumps,

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treadle pumps, low-cost bucket and drip lines, sustainable land management practices, supplemental irrigation, and recharge and use of groundwater and water harvesting systems. Of the many studies that documented the poverty reduction impacts of micro-irrigation in Asia, Namara et al., (2007a) and Narayanamoorthy, A., (2007), both from India, reported that micro-irrigation technologies result in a significant productivity and economic gains. Shah et al. (2000) reported that treadle pump technology has had a tremendous impact in improving the livelihoods of the poor in Bangladesh, eastern India, and the Nepal Terai, South Asia's so-called "poverty square."

As far as sub-Saharan Africa is concerned, although there are specific country evidences that support the poverty reduction impacts of irrigation development (Van Koppen et al., 2005; Namara et al., 2007; Tesfaye et al., 2008; FAO, 2008), a report by AfDB, FAO, IFAD, IWMI, and the World Bank (2007) documented that irrigated cropping in the region continues to be characterized by low productivity and hence low profitability with serious implications for poverty reduction and growth.

There is an emerging literature, on the impact of small scale agricultural water management technologies on poverty in Africa. Just to mention few: Evidences from Tanzania, suggest that acquisition of a pump enabled households to double their income (Van Koppen et al., 2005). Similarly, Adoption of treadle pumps by farmers in Niger has resulted in significant positive impacts, in terms of improvement of labor efficiency, increase in area under cultivation, cropping intensity and production volume, and increase in farm income. In Nigeria, a combination of "before-after" and "with-without" project comparisons showed that the use of low cost petrol pumps had a positive effect on its direct beneficiaries and slightly improved their situation in terms of income derived from irrigated fadama farming (Van Koppen et al., 2005). On the impact of use of treadle pump in Ghana, West Africa, Adeoti, et al., (2007), using a "with and without" approach found that adoption of treadle pumps reduces poverty as measured by household income. A positive impact on human capital was realized as incomes were used to pay for children's schooling and for health care.

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Of the many studies that documented the poverty impact of micro-irrigation in Asia, Hussain, et. al. (2001) reported that there has been an upsurge in the adoption of irrigation technologies for smallholders such as low-cost pumps, treadle pumps, low-cost bucket and drip lines, sustainable land management practices, supplemental irrigation, and recharge and use of groundwater and water harvesting systems. Namara et al., (2007a) and Narayanamoorthy, A., (2007), both from India, reported that micro-irrigation technologies result in a significant productivity and economic gains. Shah et al. (2000) reported that treadle pump technology has had a tremendous impact in improving the livelihoods of the poor in Bangladesh, eastern India, and the Nepal Terai, South Asia's so-called "poverty square." ¶

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scarcity of evidence, particularity in Africa, in the literature that measured the poverty impacts of AWMTs in general and makes a qualified discussion of the impact of different forms of AWMTs on poverty. The few existing evidences from elsewhere seem to support the stipulated positive effects.

In this study, we explored whether adoption of AWM technologies has led to such improvements and if so we identified which technologies have relatively higher impact. Welfare indicators such as per capita income and expenditure per adult equivalent were used to measure these improvements. To explore the impact of adoption of AWMT on poverty we used simple and complex statistical techniques ranging from simple mean separation tests, estimation of average treatment effects using propensity score matching and standard poverty analysis. Hence, the paper quantified the effect on poverty of successfully adopting AWMT. We analyzed the state of poverty among sample farm households with and without access to agricultural water management technologies while also understanding the correlates of poverty using a multivariate regression model. The paper also quantified the average treatment effect of using AWMTs.

The study used a unique household level data of 1517 households from 29 Peasant Associations (Kebele) [2] in four regional states in Ethiopia, where these technologies are widely practiced (see Fig. 1). The survey was conducted during Oct-Dec. 2007. The paper is organized as follows. Section two outlines the methodological approaches used

[2] Kebele in average covers 800ha of land and the lowest rural administrative system in Ethiopia and also known as peasant association

in this paper to measure impact. In section three we present statistical summary and mean separation test results of important variables; the findings of the matching econometrics; and the poverty estimates and their decomposition by different socio-economic variables, and stochastic dominance tests. Section four presents the results of the determinants of poverty analysis from a multivariate regression analysis. The final part concludes and draws policy recommendations.

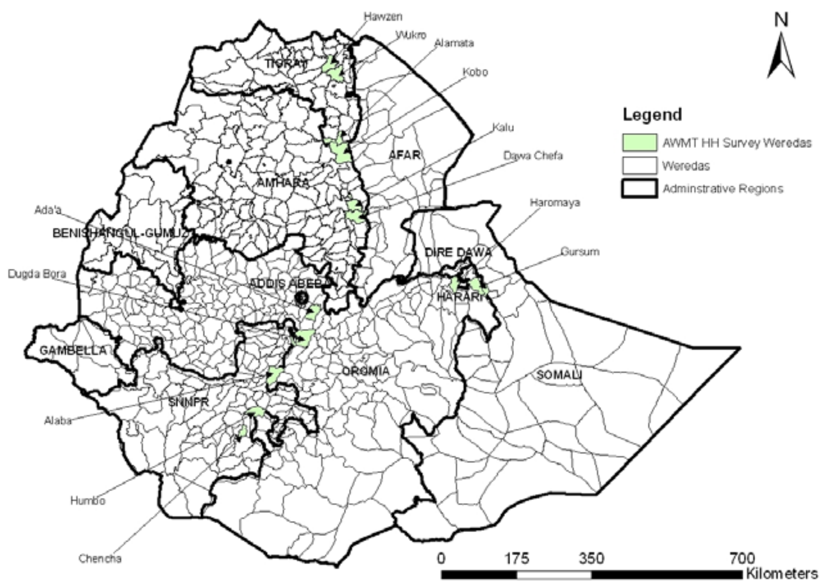

Figure 1: Location of the study sites

2. Materials and methods

Data sources

This study is part of a comprehensive study on Agricultural Water Management Technologies in Ethiopia. The study includes inventory of Agricultural Water Management Technologies and Practices in Ethiopia and assessment of the poverty impacts of most promising technologies, the focus of this study being on the latter. The study was conducted during October - December 2007 and was implemented by the International Water Management Institute (IWMI) with support from USAID. The socio-economic survey data, on which this paper is based, is gathered from a total sample of 1517 households from 29 Peasant Associations (PAs) in four Regional states. The PAs were selected based on the presence of identified promising technologies. Then the households from each PA were selected based on the criterion of their access to AWM technologies vs. no access using non-proportional random sampling. Details of the sample households by type of technologies from the four regions are given below in table 1. This selection was based first on the identification of promising technologies through key informant interviews (see Loulseged, et al. 2008). The data was collected for the 2006/2007 cropping season.

Table 1: Summary of sample households

Region	**Agricultural water management technologies**						
	Purely rainfed	Pond	Shallow wells	Deep wells	River diversion	Micro dams	others
Amhara	281	8	45	10	28	13	5
Oromia	219	12	23	68	68	1	2
SNNPR	217	68	55	0	14	25	0
Tigray	143	47	91	1	40	35	18
Total	688	829					

Methodology

The poverty impacts of AWMT were assessed first using simple mean separation tests on key variables (per capita income, expenditure per adult equivalent, income from cash crop sales, perceived changes in food security, farm input use and asset holding). We then examined the impact of AWMT on household wellbeing, where wellbeing is measured as per capita household income, using matching econometrics. Finally we undertook poverty analysis using standard poverty analysis techniques to explore whether those with access to AWT are relatively better-off compared to those without access. We briefly present the matching and poverty analysis approaches used below.

Propensity score matching

One of the problems of assessing impact is to find comparable groups of treated and control groups, i.e. users and non-users of AWMT. Matching econometrics provides a promising tool to do just that while estimating the average treatment effects (Ravallion, 2004).

Matching is a method widely used in the estimation of the average treatment effects of a binary treatment on a continuous scalar outcome. It uses non-parametric regression methods to construct the counterfactual under an assumption of selection on observables. We think of having access to AWM technologies as a binary treatment, income per capita as an outcome, and households having these technologies as treatment group and non-user households as control group. Matching estimators aim to combine (match) treated and control group households that are similar in terms of their observable characteristics in order to estimate the effect of participation as the difference in the mean value of an outcome variable. In this case, we used observable household characteristics (such as characteristics of household head, land, livestock and labour endowment, access to credit, etc.) and village level covariates that may influence choice of participation in the intervention (e.g. choice of AWMTs) but not necessarily influenced by the intervention.

Following the literature of program evaluation, let Y_1 is the per capita income when household i is subject to treatment $(C=1)$ and Y_0 the same variable when a household is exposed to the control $(C=0)$. The observed outcome is then

$$Y = CY_1 + (1-C)Y_0 \tag{1}$$

When $C=1$ we observe Y_1; when $C=0$ we observe Y_0. Our goal is to identify the average effect of treatment (using AWMT) on the treated (those households who have access to the technologies) (ATT). It is defined as

$$ATT = E(Y_1 - Y_0 | C=1) = E(Y_1 | C=1) - E(Y_0 | C=1) \qquad (2),$$

The evaluation problem is that we can only observe $E(Y_1 | C=1)$; however, $E(Y_0 | C=1)$ does not exist in the data, since it is not observed. A solution to this problem is to create the counterfactual $E(Y_0 | C=1)$ (what would have been the income of households with access to AWMT had they not had access (or the converse)), by matching treatment and control households. As discussed by Heckman (1998) a critical assumption in the evaluation literature is that no-treatment state approximates the no program state[3]. For matching to be valid certain assumptions must hold. The primary assumption underlying matching estimators is the Conditional Independence Assumption (CIA). CIA stated that the decision to adopt is random conditional on observed covariates X. In notation,

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

This assumption imply that the counterfactual outcome in the treated group is the same as the observed outcomes for non-treated group

[3] Here the assumption of no contamination bias or general equilibrium effect is important.

$$E(Y_0|X, C=1) = E(Y_0|X, C=1) = E(Y_o|X) \quad (4)$$

This assumption rules out selection into the program on the basis of unobservables gains from access. The CIA requires that the set of X's should contain all the variables that jointly influence the outcome with no-treatment as well as the selection into treatment. Under the CIA, ATT can be computed as follow:

$$ATT = E(Y_1 - Y_0|X, C=1) = E(Y_1|X, C=1) - E(Y_0|C=1) \quad (5)$$

Matching households based on observed covariates might not be desirable or even feasible when the dimensions of the covariates are many. To overcome the curse of dimensionality, Rosenbaum and Rubin (1983) show that instead of matching along X, one can match along $P(X)$, a single index variable that summarizes covariates. This index is known as propensity score (response probability). It is the conditional probability that household i adopts AWMT given covariates:

$$p(X) = pr(C=1)|X \quad (6)$$

The ATT in equation (5) can then be written as

ATT= $E(Y_1|P(X), C=1) - E(Y_0|P(X), C=1)$ (7)

The intuition is that two households with the same probability of adoption will show up in the treated and untreated samples in equal proportions. The propensity score (pscore) is estimated by a simple binary choice model; in this paper a binary Logit model is used. Once the pscore is estimated, the data is split into equally spaced intervals (also called common support) of the pscore. Within each of these intervals the mean pscore and of each covariate do not differ between treated and control plots. This is called the balancing property. For detail algorithm of pscore matching see Dehejia and Wahba (2002). If the balancing property is not satisfied higher order and interaction terms of covariates can be considered until it is satisfied. Since pscore is a continuous variable exact matches will rarely be achieved and a certain distance between treated and untreated households has to be accepted. To solve this problem treated and control households are matched on the basis of their scores using nearest neighbor, kernel and stratification matching estimators. These methods identify for each household the closest propensity score in the opposite technological status; then it computes investment effect as the mean difference of household's income between each pair of matched households. For details of these methods we refer to Becker and Ichino (2002) who also provide the STATA software code we use in this paper. One limitation of the matching based on observables is that endogenous program placement due to purposive targeting based on unobservables will leave bias (Ravallion, 2001). However, there is hardly reason to believe that these interventions are purposively placed as the feasibility of the technologies is conditioned more by natural factors (e.g. availability of water, topography, etc.) than by socio-economic preconditions.

Poverty analysis

When estimating poverty following the money metric approach to measurement of poverty, one may have a choice between using income or consumption as the indicator of well-being. Most analysts argue that, provided the information on consumption obtained from a household survey is detailed enough, consumption will be a better indicator of poverty measurement than income for many reasons (Coudouel et al. 2002). Hence, in this paper we estimate poverty profiles using expenditure adjusted for differences in household characteristics.

Constructing poverty profiles

We used the Foster-Greer-Thorbecke (FGT) class of poverty measures to calculate poverty indices. The FGT class of poverty measures have some desirable properties (such as additive decomposability), and they include some widely used poverty indices (such as the head-count and the poverty gap measures). Following Duclos et al. (2006), the FGT poverty measures are defined as

$$\mathrm{P}(\mathrm{z};\alpha) = \int_0^1 \left(\frac{g(p;z)}{z} \right)^{\alpha} dp \qquad (8)$$

where z denotes the poverty line, and α is a nonnegative parameter indicating the degree of sensitivity of the poverty measure to inequality among the poor. It is usually referred to as poverty aversion parameter. Higher values of the parameter indicate greater sensitivity of the poverty measure to inequality among the poor. The relevant values of α are 0, 1 and 2.

At α =0 equation 8 measures poverty incidence or the head count ratio. This is the share of the population whose income or consumption is below the poverty line, that is, the share of the population that cannot afford to buy a basic basket of goods, food or non-food or both depending on which one is interested in.

At α =1 equation 8 measures depth of poverty (poverty gap). This provides information regarding how far off households are from the poverty line. This measure captures the mean aggregate income or consumption shortfall relative to the poverty line across the whole population. It is obtained by adding up all the shortfalls of the poor (assuming that the non-poor have a shortfall of zero) and dividing the total by the population. In other words, it estimates the total resources needed to bring all the poor to the level of the poverty line (divided by the number of individuals in the population). Note also that, the poverty gap can be used as a measure of the minimum amount of resources necessary to eradicate poverty, that is, the amount that one would have to transfer to the poor under perfect targeting (that is, each poor person getting exactly the amount he/she needs to be lifted out of poverty) to bring them all out of poverty (Coudouel et al. 2002).

At $\alpha = 2$ equation 1 measures poverty severity or squared poverty gap. This takes into account not only the distance separating the poor from the poverty line (the poverty gap), but also the inequality among the poor. That is, a higher weight is placed on those households further away from the poverty line.

We calculated these indices using STATA 9.0 and tested for difference between poverty profiles between groups following approaches suggested by Kwakani (1993) and Davidson and Duclos (1998).

Dominance tests

Poverty comparisons can, however, be sensitive to the choice of the poverty line. The important issue in poverty analysis is that the poverty line yields consistent comparisons (Ravallion, 1994). Stochastic tests used to check the robustness of ordinal poverty comparisons prove to be useful in poverty analysis (Atkinson, 1987). The idea of standard welfare dominance is to compare distributions of welfare indicators in order to make ordinal judgment on how poverty changes (spatially, inter-temporally or between groups) for a class of poverty measures over a range of poverty lines (Ravallion, 1994; Davidson and Duclos, 2000). Hence, we need to undertake ordinal poverty comparisons using stochastic dominance tests and check the robustness of the poverty orderings. The idea here is to make ordinal judgments on how poverty changes for a wide class of poverty measures over a range of poverty lines.

Determinants of poverty

An analysis of poverty will not be complete without explaining why people are poor and remain poor over time. Within a microeconomic context, the simplest way to analyze the correlates of poverty consists in using a regression analysis against household and demographic factors, specific individual/household head characteristics, asset holdings, village level factors, and access to services (markets, credit, AWM technologies, extension, etc). Let the welfare indicator W_i be gives as:

$$W_i = Y_i / Z \tag{9}$$

where Z is the poverty line and Y_i is the consumption expenditure per adult equivalent. Denoting by X_i the vector of independent variables, the following regression

$$LogW_i = \beta' X_i + \varepsilon_i \tag{10}$$

could be estimated by ordinary least squares (OLS). In this regression, the logarithm of consumption expenditure (divided by the poverty line) is used as the left-hand variable. The right hand variables in the regressions include: (a) household head characteristics, including sex, level of education (using five tiered categories), primary occupation of the household (farming vs. non-farming) and consumer worker ratio; (b); asset holding: oxen holding, livestock size (in TLU[4]) and farm size, adult labor (by sex) all in per adult equivalent terms; c) access to different services and markets: credit, non-farm employment, access to market proxied by distance to input markets, seasonal and all weather roads, distance to major urban markets; and d) village level characteristics mainly agro-ecology.

[4] We used livestock less oxen in Tropical livestock units.

The β coefficients in equation (10) are the partial correlation coefficients that reflect the degree of association between the variables and levels of welfare and not necessarily their causal relationship. The parameter estimates could be interpreted as returns of poverty to a given characteristics (Coudouel et al., 2002; Wodon, 1999) while controlling for other covariates, the so-called ceteris paribus condition. We used regression techniques to account for the stratified sampling technique and, hence, adjust the standard errors to both stratification and clustering effects (Deaton; 1997; Wooldrige, 2002) and thereby to deal with the problem of heteroskedasticity. We also tested for other possible misspecifications (e.g. multicollinearity) using routine diagnostic measures.

In summary the analysis of poverty and inequality followed six steps. First, we have chosen household consumption expenditure as welfare measure and this was adjusted for the size and composition of the household. Second, the consumption poverty line was set at 1821.05 Birr (1USD=9.2 Birr), an inflation-adjusted poverty line of the official baseline poverty line of ETB 1075 set in 1995/96 as measure of welfare corresponding to some minimum acceptable standard of living in Ethiopia (MOFED, 2006). We also used an inflation-adjusted poverty line of 1096.03 as absolute food poverty line based on the corresponding 1995/96 official food poverty line. These lines were chosen to enable meaningful comparison of poverty levels in Ethiopia between various groups and over time (in reference to earlier studies). The poverty line acts as a threshold, with households falling below the poverty line considered poor and those above the poverty line considered non-poor. Third, after the poor has been identified, poverty indices such as head count, poverty gap and poverty gap squared were estimated. Fourth, we constructed poverty profiles showing how poverty varies over population subgroups (example users

Vs non-users) or by other characteristics of the household (for example, level of education, age, asset holding, location, etc.). The poverty profiling is particularly important as what matters most to policymakers is not so much the precise location of the poverty line, but the implied poverty comparison across subgroups or across time. Furthermore, we undertook ordinal poverty comparisons using stochastic dominance tests to check the robustness of the poverty orderings. This is important because the estimation of the poverty line could be influenced by measurement errors. Lastly, we explored the determinants of poverty using multivariate regression analysis. We analyzed the correlates of poverty against household and demographic factors, specific individual/household head characteristics, asset holdings including adoption and use of AWM technologies, village level factors, and policy related variables (access to services). By doing so, the marginal impact of access to AWM technologies on poverty was assessed while controlling for other possible covariates.

3. Results and discussions

Summary and separation tests

We report the results of the mean separation tests of important variables for users and non-users. This statistical test result could serve as some indicative measures of the differences in important variables between users and non-users, which may be considered as indicative measures of the impact of access to AWMT. However, we will be required to do a more systematic analysis of impact before we could draw definite conclusions on impact of access to AWMT. Accordingly, we found statistically significant difference in mean values of important variables (Table 2).

As could be seen from the mean separation test, there is statistically significant difference ($p < 0.000$) in agricultural income (both crop and livestock) among users and non-users of AWMT. Those with access to AWMT were found to use higher farm inputs and have significantly higher share of their produce supplied to the market ($p \leq 0.000$) implying increased market participation. Accordingly, the value of fertilizer, seed, labor and insecticide used and the size of loan received from microfinance institutions were significantly higher for users of AWMT compared with non-users. This may imply that because of access to AWMT, there is increased intensification of agriculture. This is expected to have wider effects on the economy e.g. on input and factor markets. Not surprisingly, users were also found to have significantly higher asset endowments such as male adult labor, oxen, livestock (in TLU) and land holding, which may imply that those with access to AWMT have managed to build assets. On the other hand, it may also mean that households with better resource endowments may be targeted by the program (or due to self-selection) secured access AWMT, an issue we may not be able to tell in the absence of baseline data. However, the mean separation test indicated that there is no significant difference in mean consumption expenditure per adult equivalent, incidence of food shortage and size of non-farm income between those with access to AWMT and those without access.

Table 3: mean separation tests of some important variables of households with access and without access to AWMT

Variable name	Non-user of AWMT (n= 641)	User AWMT (n= 876)	p-value*
	Mean (SE)	Mean (SE)	
Value of fertilizer used	274.9 (27.0)	399.5 (32.7)	0.0053
Value of seed used	272.1 (31.1)	698.1 (204.1)	0.0762
Value of labor used	600.9 (34.7)	1114.3 (67.6)	0.0000
Value of insecticide used	19.6 (3.1)	75.4 (19.7)	0.0161
Loan size (cash)	1293.4 (108.0)	1688.9 (102.5)	0.0083
Crop income	302.3 (16.4)	682.5 (57.0)	0.0000
Livestock income	51.6 (5.37)	67.3 (4.25)	0.0201
Agricultural income	352.9 (7.2)	749.7 (57.2)	0.0000
Non-farm income	63.7 (4.36)	67.0 (4.95)	0.6276
Consumption expenditure per adult equivalent (monthly)	39.2 (4.46)	40.8 (3.71)	0.7739
Face food shortage	0.373 (0.019)	0.354 (0.016)	0.4475
Market share	0.07 (0.01)	0.15 (0 .012)	0.0000
Oxen units	1.18 (0.047)	1.71 (0.055)	0.0000
Livestock units (in TLU)	3.27 (0.113)	4.64 (0.15)	0.0000
Land holding in (timad)	5.12 (0.163)	7.143 (0.19)	0.0000
Labor endowment (adult labor)	2.961 (0.059)	3.054 (0.051)	0.2340
Labor endowment (Adult male)	1.4456 (0.039)	1.568 (0.035)	0.0209
Labor endowment (Adult female)	1.496 (0.037)	1.476 (0.029)	0.6650

* Two-sided test of equality of means

The problem with such mean separation tests is non-comparability of the two sub-samples and that we did not control for the effect of other covariates. Hence, we will systematically analyze if access to AWMT has led to significant effects on income and poverty using matching (by creating comparable groups) and standard poverty analysis techniques respectively in the subsequent sections.

Average treatment effects

The matching estimates where the treated and control households were matched on the basis of their scores using nearest neighbor, kernel methods and stratification matching estimators, show that there is significant effect on household income from owning

AWMTs. Important to note is that out of the 1517 households only about 947 are comparable (see Table 3). The estimated average treatment effect for the treated (ATT) is also positive in all the cases and is about ETB 780 (equivalent to USD 82). This indicated that access to AWMT technologies has lead to significant increase in per capita income.

Table 3: Results of matching method to measure impact of AWMT on household income (bootstrapped standard errors)

Kernel Matching method				
Treatment (n)	**Control (n)**	**ATT**		**t-test**
699	394	788.674	(218.78)	3.605***
Nearest Neighbor Matching method				
699	247	760.048	(255.73)	2.972***
Stratification method				
699	394	785.326	(227.53)	3.451***

We now turn to poverty analysis using consumption expenditure per adult equivalent.

Poverty profiles and decomposition

Using the absolute overall poverty line of ETB 1821.05, about 48 percent of the individuals in user households have been identified as poor. On the other hand, about 62 percent of the individuals in non-users were identified as poor. The test results also show that there is significant difference in poverty levels between users and none users. Our calculation shows that there is about 22% less poverty among users compared to non-users. In other words, individuals with access to AWMT are in a better position to meet their consumption requirements, food and non-food. There is also significant difference in poverty gap and severity of poverty among users and non-users, implying that access to AWMT are effective instruments to narrow the poverty gap and inequality (see Table 4). However, this also implies that the level of poverty has increased compared to reported official overall poverty of about 39 % in 2004/05 (MoFED, 2006; p. 23) calculated based on poverty line of ETB 1,075. However, we feel that this seemingly significant increase in poverty has to do with the failure to adjust the poverty line to account for price changes in the cited document.

Table 4. The effect of irrigation on incidence, depth and severity of poverty (poverty line = ETB 1821.05)

Category	Incidence ($\alpha = 0$)		Depth ($\alpha = 1$)		Severity ($\alpha = 2$)	
	value	SE	Value	SE	Value	SE
Access to AWMT						
Users (n= 876)	0.478	0.017	0.198	0.009	0.1110	0.007
Non-users (n= 641)	0.623	0.018	0.282	0.011	0.167	0.009
z-statistic[*]	-484.2***		-381.6***		-282.0***	
Types AWMT[5]						
Pond (n= 196)	0.561	0.035	0.218	0.017	0.107	0.011
z-statistic[6]	-193.5***		-170.8***		-146.2***	
Shallow wells (n= 251)	0.565	0.031	0.266	0.019	0.168	0.016
z-statistic	-233.0***		-172.3***		122.1***	
Deep wells (n=93)	0.312	0.048	0.113	0.021	0.0550	0.013
z-statistic	-109.2***		-107.8***		-98.0***	
River diversion (n= 291)	0.403	0.029	0.1440	0.013	0.071	0.009
z-statistic	-258.0***		-235.5***		-189.0***	
Micro-dams (n= 63)	0.484	0.063	0.1910	0.032	0.101	0.022
z-statistic	-71.6***		-63.0***		-53.3***	
In-situ technologies						
Users (n= 368)	0.614	0.025	0.253	0.014	0.141	0.0110
Non-users (n= 373)	0.521	0.0148	0.2300	0.008	0.134	0.007
z-statistic	-296.2***		-220.9***		-150.5***	
Water application technologies[7]						
Flooding (n= 533)	0.429	0.021	0.159	0.010	0.079	0.007
Manual (n= 284)	0.567	0.029	0.274	0.018	0.171	0.015
Water withdrawal						
Treadle pump (n=101)	0.524	0.049	0.183	0.023	0.088	0.014
z-statistic	-111.0***		-103.4***		-63.4***	
Motor pump (n=127)	0.228	0.037	0.068	0.0135	0.027	0.007

[*] The z-statistic is derived using Kwakani's (1993) formulae to test for equality of poverty measures. The critical value for the test statistic is 1.96 (applicable for all tests in Tables 4-6) at 5% level of significance.
[5] We compared those using different AWMT against non-users.

[7] We compared those using different water application technologies against non-users.

z-statistic	-155.7***		-172.7***		-171.0***	
Water input						
Supplementary (n= 270)	0.56	0.030	0.262	0.18	0.16	0.15
z-statistic	-245.0***		-24.5***		-17.4***	
Full irrigation (n= 579)	0.437	0.020	0.16	0.009	0.077	0.006
z-statistic	-322.7***		-287.0***		-231.7***	

We disaggregated users by the type of AWMT to measure the poverty impact of specific technologies. As could be seen from the reported results, all ex-situ technologies considered in this study were found to have significant poverty reducing impacts. However, deep wells, river diversions and micro dams seem to have higher poverty impacts compared to ponds and shallow wells perhaps largely due to scale benefits. In this case, deep wells, river diversions and micro dams have led to 50, 32 and 25 percent reduction in poverty levels compared to the reference, i.e. rain fed system. On the other hand, use of in-situ AWMT was found to have no significant poverty reducing impacts. On the contrary, those using in-situ AWMT are found to have higher poverty levels in terms of the head count, poverty gap and severity of poverty indices. We do not have any a priori reason for this seemingly counter intuitive result. However, it may be mentioned that in-situ technologies have been used as mere soil conservation measures with little immediate impact on productivity growth; and at the same time they may divert labor from direct agricultural crop production.

We also considered disaggregating poverty levels by type of water withdrawal and application technologies. The most common withdrawal and application mechanisms include gravity flooding (63.3 %), manual (33.7 %), treadle pump (6.7%), and motor pump (8.4%). Sprinkler (0.20 %) and drip (0.20%) are hardly practiced although there are signs of households picking up these technologies gradually. Accordingly, those using motor pumps were found to have significantly lower poverty level, compared to treadle pump users. In fact, as a result of using motorized pumps, there is more than 50 percent reduction in the incidence of poverty mainly due increased water availability and scale benefits. As far as, water application technologies are concerned, households using gravity were found to have significantly lower poverty levels compared to those using manual (using cans) applications. Furthermore, we disaggregated poverty by the type of water use that is whether water is used for supplementary or full irrigation. Our results show that those who use AWMT for full irrigation have significantly lower poverty levels compared to those using supplementary and non-users. This implies that supplementary irrigation could contribute to poverty reduction; a significant contribution comes, however, from full irrigation. System reliability and scale benefits seem to be the most important drivers of poverty reduction. This will have an important implication on technology choice for an effective poverty reduction.

We also estimated poverty profiles using an absolute food poverty line of ETB 1096.02. Accordingly, 23 percent of the users and 34 percent of the non-users respectively are identified as food poor. These indices could be taken as food security indices. This implies that the level of food security has increased compared to 38% in 2004/05 (MoFED, 2006; p. 27) calculated based on poverty line of ETB 647.8. However, we feel that the food poverty line used should have been adjusted to account for price changes to make meaningful comparisons.

When disaggregated by type of AWMT, as in the case of overall poverty, deep wells, river diversion and micro dams have relatively higher impact on reducing food poverty. Ponds and wells, although have led to significant reduction (compared to non-users), they have relatively lower poverty reducing impacts. However, in-situ AWMT have not led to significant reduction to food insecurity. On the contrary, those using in-situ AWMT are found to have higher poverty levels in terms of the head count, poverty gap and severity of poverty indices.

Table 5: The effect of irrigation on incidence, depth and severity of poverty (poverty line = ETB 1096.02)

Category	Incidence ($\alpha = 0$)		Depth ($\alpha = 1$)		Severity ($\alpha = 2$)	
	value	SE	Value	SE	Value	SE
Access to AWMT						
Users (n= 876)	0.2340	0.015	0.086	0.007	0.049	0.005
Non-users (n= 641)	0.349	0.018	0.137	0.009	0.081	0.007
z-statistic*	-286.4***		-231.3***		-181.8***	
Types AWMT						
Pond (n= 196)	0.275	0.032	0.071	0.011	0.028	0.006
z-statistic[8]	-116.2***		0.00		-144.9***	
Shallow wells (n= 251)	0.311	0.029	0.143	0.017	0.094	0.014
z-statistic	-137.0***		0.0		-69.7***	
Deep wells (n= 93)	0.151	0.037	0.0380	0.0130	0.017	0.008
z-statistic	-3.8***		0.0		-73.2***	
River diversion (n= 291)	0.158	0.021	0.047	0.008	0.023	0.006
z-statistic	-179.6***		0.0		-128.9***	
Micro-dams (n= 63)	0.234	0.053	0.081	0.022	0.039	0.014
z-statistic	-47.0***		0.0		-39.7***	
In-situ technologies						
Users (n= 368)	0.302	0.024	0.111	0.012	0.062	0.009
Non-users (n= 373)	0.279	0.013	0.109	0.007	0.064	0.005
z-statistic	-156.7***		-117.2***		-85.1***	
Water application technologies						
Flooding (n= 533)	0.176	0.016	0.056	0.006	0.027	0.005
Manual (n= 284)	0.341	0.028	0.144	0.015	0.091	0.0128
Water Withdrawal technologies						
Treadle pump (n=101)	0.227	0.042	0.062	0.013	0.020	0.005
z-statistic	-490.7***		0.1		-104.6***	
Motor pump (n= 127)	0.0470	0.019	0.014	0.007	0.006	0.003
z-statistic	-490.8***		0.0		-149.3***	

* Critical statistics

[8] We compared those using different AWMT against non-users.

Water input						
Supplementary (n= 270)	0.333	0.028	0.138	0.016	0.086	0.013
z-statistic	-496.6***		0.1		-75.8***	
Full irrigation (n= 579)	0.174	0.0158	0.053	0.006	0.025	0.004
z-statistic	-490.7***		0.1		-155.8***	

Furthermore, households using AWMT for full irrigation have relatively lower food poverty compared to those using water for supplementary irrigation. We also conclude that the mentioned comparative advantages are linked to reliability and adequacy of water supply as well as availability of labor for water management.

Who are the Poor?

We tried to gain additional insights into the question of who the poor are by decomposing poverty profiles of households by other socio-economic variables. We used variables such as sex of the household head, education status of the head, asset holding (mainly labor, farm and oxen holding) and access to services like formal credit and location dummies (in this case regions). We tested for differences in poverty across socio-economic groups using statistical tests. The results are reported in Table 6.

The regional decomposition of poverty shows that users of AWMT in Oromia and Amhara have significantly lower poverty levels in incidence, depth and severity of poverty compared to users in Tigray and SNNPR. This may show the successful use of AWMT in Oromia and Amhara having significant impact on poverty reduction. Not surprisingly, poverty seems to be closely related to asset holding, most importantly land holding. Households with operated farm holding greater than the mean holding, depicted lower poverty levels than those having farm holding less than the mean. On the other hand, households with oxen holding greater or equal to the mean holding (1.5 oxen units) displayed significantly higher poverty levels, perhaps indicating owning more than two oxen may not contribute to poverty reduction. Female-headed households have apparently higher poverty levels in terms of the incidence, depth and severity of poverty.

Table 6: Poverty decomposition by other socio-economic variables (users only and poverty line = ETB 1821.05)

Variables	Incidence ($\alpha = 0$)		Depth ($\alpha = 1$)		Severity ($\alpha = 2$)	
	value	SE	Value	SE	Value	SE
Tigray region (n= 244)	0.606	0.031	0.215	0.015	0.102	0.009
z-statistic	-230.5***		-202.0***		-179.3***	
Amahra region (n= 273)	0.329	0.028	0.117	0.012	0.056	0.008
z-statistic	-258.7***		-2.42.8***		-198.9***	
Oromia region (n= 190)	0.258	0.032	0.081	0.012	0.036	0.007
z-statistic	-205.2***		-216.0***		-193.4***	
SNNPR region (n= 169)	0.810	0.030	0.446	0.026	0.301	0.023
z-statistic	-205.6***		-115.4***		-78.6***	
Female-headed (n= 81)	0.568	0.055	0.205	0.028	0.107	0.020
Male-headed (n= 768)	0.463	0.018	0.191	0.009	0.106	0.007
z-statistic	-67.9***		-55.4***		42.8***	
Education level of head						
Illiterate (n= 787)	0.59	0.175	0.27	0.011	0.162	0.008
Informal education (n= 239)	0.47	0.03	0.174	0.015	0.085	0.009
z-statistic	-56.9***		-127.4***		-0.2***	
Primary complete (n= 327)	0.49	0.027	0.203	0.015	0.119	0.012
z-statistic	-62.8***		-165.9***		-125.3***	
Junior complete (n= 119)	0.48	0.046	0.20	0.024	0.106	0.017
z-statistic	-45.3***		-76.9***		-57.3***	
10 & above complete (n= 29)	0.44	0.094	0.187	0.055	0.121	0.046
z-statistic	-18.0***		-17.4***		-13.7***	
Primary occupation						
Farming (n= 834)	0.48	0.017	0.195	0.009	0.11	0.006
Non-farming (n= 33)	0.57	0.087	0.28	0.049	0.158	0.034
z-statistic	-35.7***		-31.5***		-25.7***	
Land holding						
Below average (n= 1054)	0.55	0.15	0.247	0.009	0.147	0.002
Above average (n= 463)	0.52	0.02	0.212	0.012	0.113	0.009
z-statistic	-93.1***		-253.7***		-235.3***	
Oxen holding						
Below average (n= 691)	0.48	0.02	0.18	0.009	0.092	0.006
Above average (n= 826)	0.59	0.17	0.28	0.011	0.174	0.008
z-statistic	-89.6***		-390.3***		-343.4***	
Labor holding (male)						

Below average (n= 568)	0.64	0.02	0.29	0.012	0.175	0.010
Above average (n= 949)	0.48	0.016	0.202	0.008	0.113	0.006
z-statistic	-352.5***		-264.2***		-183.8***	
Credit access						
With access (n= 447)	0.52	0.023	0.226	0.003	0.131	0.010
Without access (n= 1070)	0.55	0.015	0.240	0.008	0.139	0.006
z-statistic	-355.1***		-620.8***		-211.6***	

Education was also found to have significant effect on poverty levels of users. Accordingly, households with heads that have informal training or higher educational attainment have lower poverty levels compared to illiterate heads. There is also a significant difference in incidence, depth and severity of poverty depending on whether households have access to formal credit. This may have to do with the fact that households with access to AWMT may use credit to purchase farm inputs. Perhaps surprisingly, households whose primary occupation is farming have significantly lower poverty in terms of the incidence, depth and severity of poverty compared to those having non-farming as their primary occupation, which signifies agriculture is the most paying occupation in rural Ethiopia. The later group mainly constitute landless farmers who make a living mainly from off/non-farm employment though they are also engaged in agricultural by renting in/sharecropping in land.

Dominance test results

Comparing the head count ratios between users and non-users of AWMT, the different orders of stochastic dominance tests established unambiguously that poverty is significantly lower among users compared to the non-users (Figure 1). This confirms that the incidence of poverty is significantly lower among users compared with non-users.

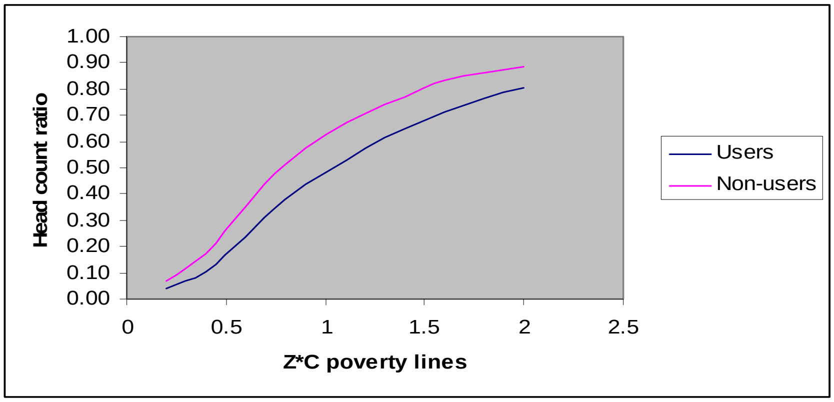

Figure 1: First-order stochastic dominance

Similarly, in terms of the depth and severity of poverty, the second and third order stochastic dominance tests showed that there was a significant difference in poverty gap and severity between users and non-users (see Figures 2 and 3). The results are robust for the different poverty lines considered. Hence, we could conclude that access to AWMT has led to significant reduction in poverty. More interestingly, AWMT are not only poverty reducing but also inequality reducing, as could be seen from the third order stochastic dominance.

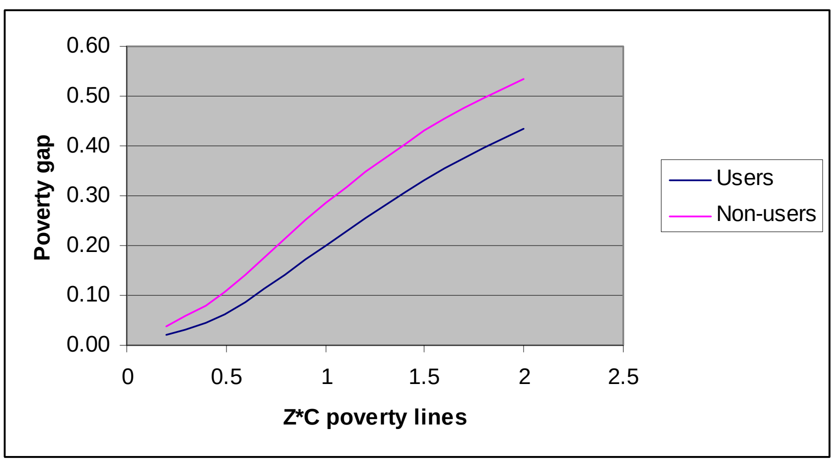

Figure 2: Second-order stochastic dominance

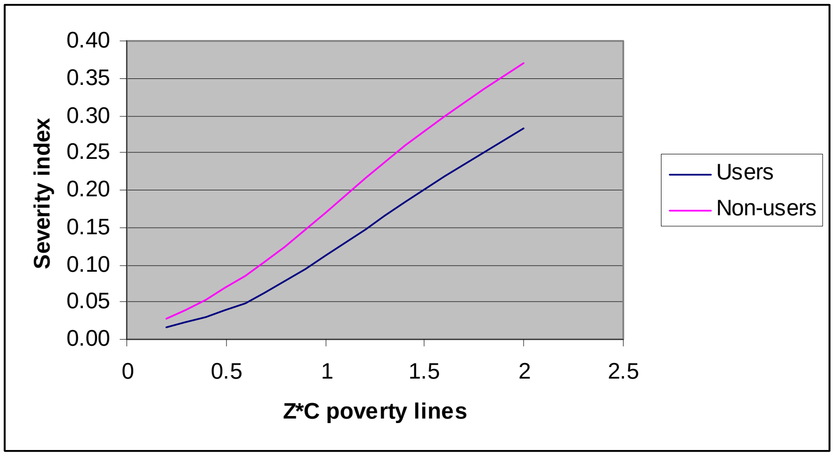

Figure 3: Third-order stochastic dominance

Poverty correlates

The results of the regression analysis on correlates of poverty are reported below. The F-test results indicate that the hypothesis of no significant β coefficient (except the intercept) is rejected (p < = 0.000); the coefficients are jointly significantly different from zero. As could be seen from the results in Table 8, most of the coefficients are significantly different from zero. The goodness of fit measure indicates that about 25 percent of the variation in the model is explained by the chosen model. Given the data used is survey data, this measure is not atypical.

Reporting on the significant variables, water input from AWMT has a significant effect on household welfare. Particularly, households that use AWMT as supplementary or full irrigation have significantly better wellbeing compared with those who depend on rainfed agriculture. This result corroborates the evidence we found earlier on the positive and poverty reducing impact of AWMT in Ethiopia.

While controlling for all other variables, households with more asset holdings are found to have significantly higher wellbeing (i.e. less poverty). This is particularly true with oxen holding and other forms of livestock holding. On the other hand, households with more adult labor endowment, both male and female, are found to have significantly lower wellbeing. This could be indicative of the high level of rural unemployment prevalent in Ethiopia and the poor functioning of the labor market.

Access to services is also found to have significant effect on household wellbeing. In this line, distance to input (fertilizer and seed) markets have a significant negative (at 1 percent level of significance) effect on household wellbeing while controlling for all other factors. Distance to water source has also a negative and significant effect on household welfare which may imply that those with access to water closely to home are better off. This underlines the fact that access to water for productive and consumptive uses, poverty reduction and sustainable livelihoods for rural people are all intimately linked (IWMI, 2007). Accesses to credit markets also have a significantly positive effect on household welfare, albeit at 10 percent level of significance. On the other hand, households distance to all weather roods has a significant and positive effect on wellbeing. The result is counter intuitive; one possible explanation could be households who are able to produce for the market transport their produce to distant but more attractive markets (Hagos et al., 2007).

Few household level covariates and agro-ecology (a village level covariate) were also found significant in explaining household wellbeing ceteris paribus. Accordingly, age of the household head has a negative effect on household welfare and this effect increases with age as we could see from the non-linear age coefficient. Our results also show that households with more dependents (compared to producers), i.e. higher consumer-worker ratio, are worse off. Education attainment of the household head has also a positive and significant effect on household welfare. Accordingly, compared to illiterate household heads, household with informal education (church and literacy program) and primary complete have a significantly positive effect on household wellbeing. The coefficients for junior high and high school complete have also the expected positive sign but were not significantly different from zero. Contrary to usual expectation, we did not find a significant difference between male-headed and female-headed in terms of welfare while controlling for all other relevant factors. Agroecology, which could be a good proxy of the agricultural potential of geographical area, was found to have a significant effect on poverty. Accordingly, households located in highland (dega) were found to have higher poverty compared to lowlands. This could be indicative of the suitability of AWMT in relatively low land compared to highlands.

Table 8: Determinants of poverty (Regression with robust standard errors)

Dependent variable: log(welfare)			
Variable name	**Coefficient**	**Standard error**	**t-value**
Household characteristics			
sex of head (Male-headed)	-0.045	0.077	-0.59
Age of head	-0.025	0.009	-2.81***
Age squared	0.0002	0.0001	2.48***
Informal education (reference illiterate)	0.162	0.056	2.90***
Primary complete(reference illiterate)	0.111	0.063	1.77*
Junior high complete (reference illiterate)	0.119	0.108	1.10
Secondary and above (reference illiterate)	0.195	0.198	0.99
Framing (reference non-farming)	-0.063	0.129	-0.49
Consumer-worker ratio	-0.096	0.031	-3.14***
Asset holding			
Number of male Adult labor	-0.077	0.030	-2.54***

Number of female Adult labor	-0.148	0.032	-4.63***
Land holding per adult equivalent	-0.0002	0.035	-0.01
Oxen per adult equivalent	0.160	0.079	2.02**
Other forms of livestock per adult equivalent (in TLU)	0.118	0.038	3.10***
Agricultural water management technologies (reference= rain fed)			
Supplementary irrigation	0.171	0.074	2.31**
Full irrigation	0.281	0.050	5.59***
Other uses (livestock and domestic)	-0.120	0.127	-0.95
Access to factor markets			
Off-farm employment	-0.048	0.049	-0.99
Credit access	0.088	0.051	1.71*
Distance to input distribution center	-0.002	0.001	-3.17***
Distance to all weather road	0.002	0.001	2.55***
Distance to local wereda center	0.001	0.001	1.28
Distance to water source	-0.003	0.001	-4.81***
Village level factors			
Agro-ecology (Weina Dega)	-0.058	0.047	-1.23
Agro-ecology (Dega)	-0.700	0.116	-6.05***
_cons	1.114351	0.273	4.07***
Number of obs = 1421 F(25, 1420) = 15.45 Prob > F = 0.0000 R-squared = 0.2517 Number of clusters = 1421			

4. Conclusions and recommendations

AWMT have been identified as important tools to mitigate adverse effects of climatic variability and to reduce poverty. Huge resources are being allocated to develop and promote diverse low cost technologies in many developing countries including Ethiopia. In the last few years, thousands of low cost AWMTs have been developed for use by smallholders. In spite of these huge investments, their impacts remain unknown. The main objective of this paper was, hence, to explore whether adoption of selected AWMTs has led to significant reduction in poverty and if so identify which technologies have relatively higher impact. The importance of such study is to identify technologies that are promising for future investments.

Our results show that there was significant reduction in poverty due to adoption and use of AWMTs. In fact, our calculations show that there is about 22% less poverty among users compared to non-users of AWMT. We found the poverty orderings between users and non-users are statistically robust. Furthermore, from the poverty analysis (severity indices), we have found that AWMT are not only effectively poverty-reducing but also equity-enhancing technologies. Equitable development is good for the poor and for better performance of the economy (Ravallion, 2005).

The magnitude of poverty reduction is technology specific. Accordingly, deep wells, river diversions and micro dams have led to 50, 32 and 25 percent reduction in poverty levels compared to the reference, i.e. rain fed system. This may imply that there is a need to promote more micro dams, deep wells and river diversions for higher impact on poverty. Use of modern water withdrawal technologies (treadle pumps and motorized pumps) were also found to have strong poverty reducing potential. Households using of motorized pumps were found to have led to more than 50 percent reduction in the incidence of poverty. Similarly, households using gravity irrigation were found to have significantly lower poverty levels compared to those using manual (using cans) applications because of scale benefits. This implies that promotion of modern water withdrawal and application technologies could enhance poverty reduction.

While poverty analysis techniques do not have in-built mechanisms of creating comparable groups, and hence, could lead to attribution bias9, our results from the propensity score matching, however, indicated that the average treatment effect of using

[9] The baseline situation of users and non-users is not known, one could argue that the difference in estimated poverty levels may have to do with differences in initial conditions.

AWMT is significant and has led to an increase in per capita income which amounts to average income of USD 82.

While access to AWMT seems to unambiguously reduce poverty, our study also indicated that there are a host of factors that could enhance this impact. The most important determinants include asset holdings, educational attainment, underutilization of family labor and poor access to services and markets. To enhance the contribution of AWMT to poverty reduction, there is, hence, a need to: i) build assets; ii) human resource development; and iii) improve the functioning of labor markets and access to markets (input or output markets). These areas could provide entry points for policy interventions to complement improved access to AWMT in Ethiopia. Moreover, care is needed in choice and promotion of technologies that are not only reliable and have scale benefits but are also resilient to climate change and variability.

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