# 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 the vulnerability of households 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 a significant reduction in poverty and, if they did so, to identify which technologies have higher impacts. The study also calculated the net present value of the selected AWMT, to assess which of the AWMTs are worth investing in given that they have the promise of reducing poverty. 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 1,517 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 incidence 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%, respectively, reduction in poverty incidence compared to the reference, i.e., rain-fed systems. Although, the selected AWMTs were found to contribute to poverty reduction, we found that ponds, deep wells and small dams were not attractive from a social cost-benefit analysis perspective, implying that choices need to be made

considering their relative financial viability and poverty reduction impacts compared to other available options that could improve rain-fed agriculture. 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 resources development; and iii) improve the functioning of labor markets and access to these (input or output) markets for enhanced impact of AWMT on poverty.

## 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 yield-enhancing modern inputs. This exacerbates household's vulnerability to poverty and food insecurity. 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).

In this line, thousands of shallow wells and dozens of deep wells have been developed since 2002/2003 in Ethiopia. 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 promising interventions in view of their poverty-reduction potential.

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) 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, 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, although still very scanty compared to the evidence in Asia, 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 treadle 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. The same study also showed that in Nigeria, 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). Adeoti, et al., (2007), exploring the impact of use of treadle pump in Ghana, West Africa, found that adoption of treadle pumps reduced poverty as measured by household income with positive impacts

on human capital, i.e. children schooling and health.

The current study also aims to contribute to the emerging literature by measuring the poverty impacts of selected agricultural water management technologies in Ethiopia. This study has at least four novel features compared to earlier studies in the field. First, it makes a systematic documentation of the so-called promising technologies/practices in Ethiopia before measuring their poverty impacts. Hence, the paper quantified the effect on poverty of successfully adopting selected AWMT. In doing so, welfare indicators such as per capita income and expenditure per adult equivalent were used to measure these improvements. Second, it considered all aspects of agricultural water management technologies ranging from in-situ to ex-situ AWM technologies and practices while also considering the different suits used to control, withdraw, convey and apply water. Third, to explore the impact of adoption of AWMT on poverty we used a variety of simple and complex statistical techniques (to test robustness of results) ranging from mean separation tests, standard poverty analysis to estimation of average treatment effects using propensity score matching. In quantifying the poverty impacts, we made sure that we created comparable groups of households from those having access and those without access to AWMTs, which is critical in assessing impact of interventions. As part of explaining the role of access to AWMTs on poverty, we also identified correlates of poverty using a multivariate regression model. Last but not least, the study calculated the net present value of the selected AWMT to see how much

each of these technologies cost households, even if the full costs for accessing these technologies are not fully borne by the households. This is important in the light of assessing which of the AWMTs are worth investing in given that they have promises to reduce poverty.

The study used a sample of 1517 farm households from 29 Peasant Associations (Kebelle)[9] in four regional states in Ethiopia, where the selected technologies are widely practiced. The survey was conducted during Oct.-Dec. 2007. The paper is organized as follows. In section two we describe the data used and the study sites followed, in section three, by brief outline of the methodological approaches used in this paper to measure impact. In section four we present the major findings of the including mean separation test results of important socio-economic variables; the estimates of the average treatment effects for the treated; the poverty estimates and their decomposition by different socio-economic variables, and some stochastic dominance tests and the determinants of poverty analysis from a multivariate regression model. Section five presents the results of a simple cost benefit analysis of the selected AWMTs. The final part concludes and draws policy recommendations.

## 2. Data and study site description

This study is part of a comprehensive study on Agricultural Water Management Technologies in Ethiopia. The study includes inventory of

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[9] A Kebelle on average covers 800ha of land and is the lowest rural administrative unit in Ethiopia. It is also known as a peasant association.

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 study is based, is gathered from a total sample of 1517 households from 29 Peasant Associations (PAs) in four Regional states (see Fig. 1). The PAs were selected based on the presence of the identified promising technologies. This selection was based first on the identification of promising technologies through key informant interviews (see Loulseged, et al. 2008). Then households from each PA were selected randomly, once the households in each PA were stratified into those with access and without access, following a non-proportional sampling approach. Details of the sample households by type of technologies from the four regions are given below in table 1. The data was collected for the 2006/2007 cropping season.
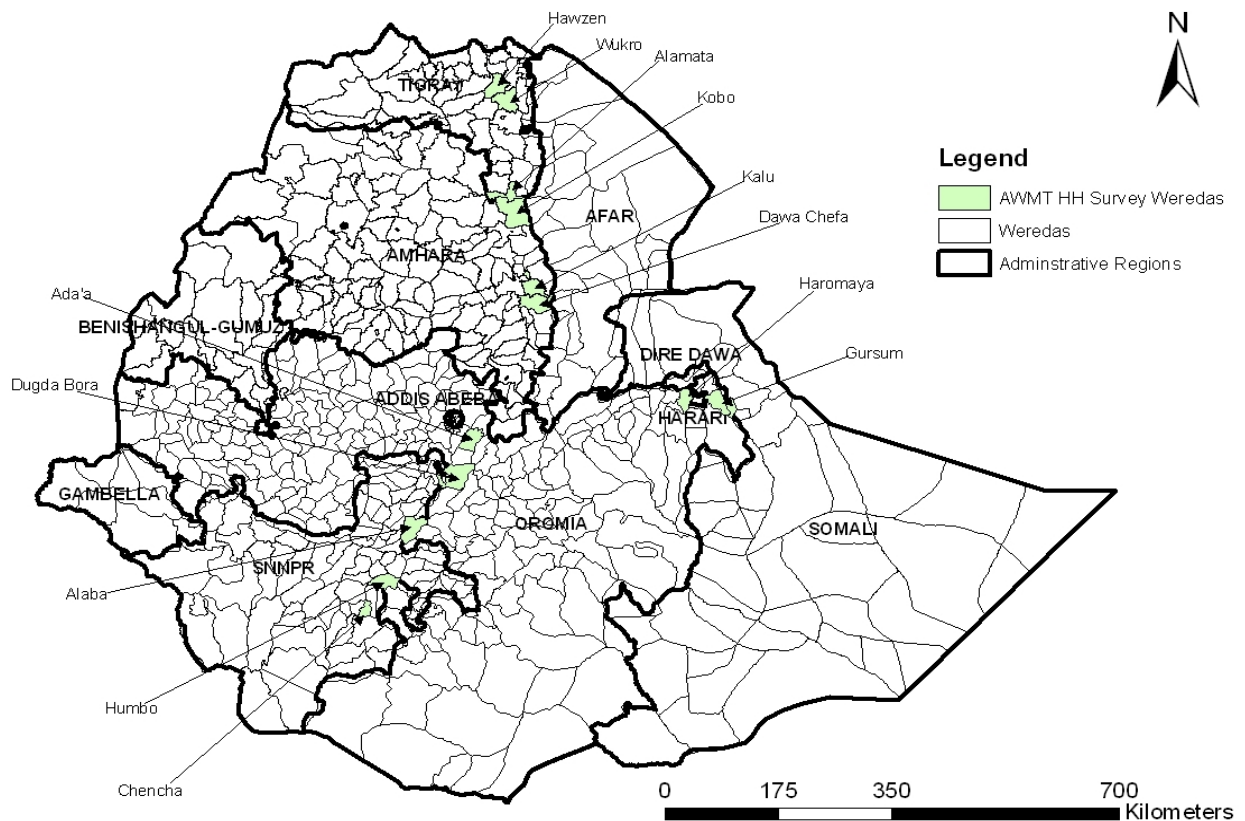


**Figure 1: Location of the study sites**

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 to establish whether access to AWMT has unambiguously led to significant increase in agricultural income which is expected to be translated to other welfare outcomes, for instance to higher consumption expenditure which we used for poverty analysis. Finally we undertook poverty analysis using standard poverty analysis techniques to explore whether those with access to AWMT have relatively higher consumption expenditure per adult equivalent compared to those without access. We briefly present the analytical methodology used for doing so below.

**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 | | | | | |

## 3. Analytical approaches

Here below we present the analytical approaches used in the paper to measure impact.

*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 labor 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

$$Y = CY_1 + (1 - C)Y_0 \qquad (1)$$

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

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

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[10]. 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,

$$(Y_1, Y_0) \perp C | X \qquad (3)$$

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

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

$$(4)$$

This assumption rules out selection into the program on the basis of unobservable 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:

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

$$(5)$$

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:

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

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

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

AT

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

(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 (p score) is estimated by a simple binary choice model; in this paper a binary Logit model is used. Once the p score is estimated, the data is split into equally spaced intervals (also called common support) of the p score. Within each of these intervals the mean p score and of each covariate do not differ between treated and control plots. This is called the balancing property. For detail algorithm of p score 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 p score 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 unobservable 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 (Foster et al., 1984). 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

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

Where z denotes the poverty line, and $\alpha$ 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 $\alpha$ are 0, 1 and 2.

At $\alpha$ =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 $\alpha$ =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:

$$W_i = Y_i / Z$$

(9)

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

$$LogW_i = \beta' X_i + \varepsilon_i$$

(10)

This 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[11]) 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.

The $\beta$ 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

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

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.

## 4. Results and discussions

In this section, we report the results of the statistical summary of important variables for users and non-users, including their test statistics, matching estimates of the average treatment effects, poverty profiles of users and non-users and decomposition by various socio-economic variables to identify who the poor are and results of the dominance tests and correlates of poverty.

*Summary and separation tests*

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 2: mean separation tests of some important variables of households with access and without access to AWMT**

| Variable name | Non-user of AWMT (n= 641) Mean (SE) | User AWMT (n= 876) Mean (SE) | p-value* |
|---|---|---|---|
| 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

Average treatment effects

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**.**

**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*** |

*, **, *** significant at 10, 5 and 1 percent level of significance

he 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. 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 incidence 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.

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 incidences 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.

**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[12]** | | | | | | |
| Pond (n= 196) | 0.561 | 0.035 | 0.218 | 0.017 | 0.107 | 0.011 |
| z-statistic[13] | -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[14]** | | | | | | |
| 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 |
| 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*** | |

*, **, *** significant at 10, 5 and 1 percent level of significance

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

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

Accordingly, those using motor pumps were found to have significantly lower poverty incidence, 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 incidence 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 incidence 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.

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.

**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[15] | -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*** | |
| **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*** | |

*, **, *** significant at 10, 5 and 1 percent level of significance

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[*] Critical statistics

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

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*** | |

*, **, *** significant at 10, 5 and 1 percent level of significance

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 constitutes 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 2). This confirms that the incidence of poverty is significantly lower among users compared with non-users.
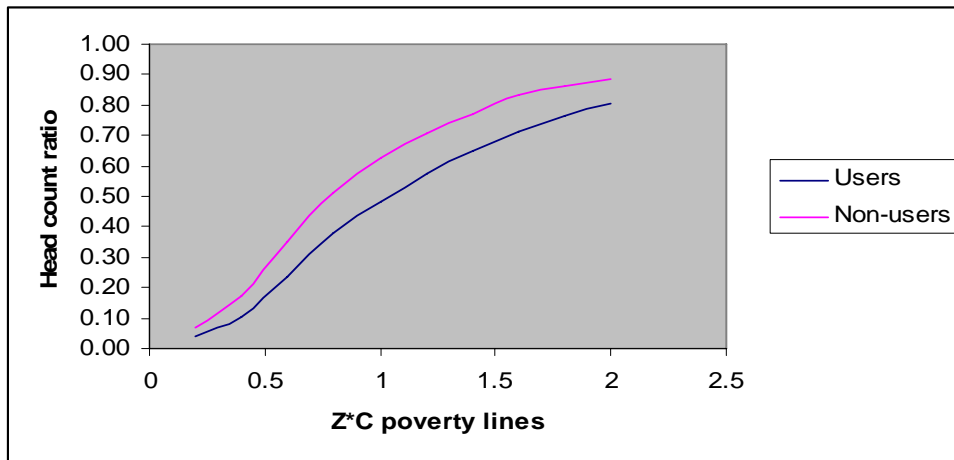


**Figure 2: First-order stochastic dominance**

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.
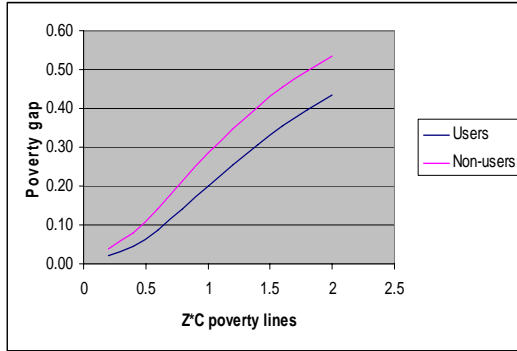
201

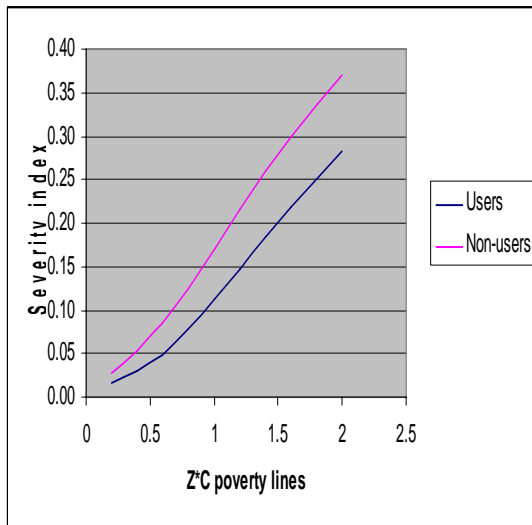**Figure 3: Second-order stochastic dominance**



**Figure 4: 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 $\beta$ 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 7, 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 rain fed 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. Agro ecology, 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 7: 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
*, **, *** significant at 10, 5 and 1 percent level of significance

## 5. AWMTs: Benefits versus costs

In the light of assessing which of the selected AWMTs are worthwhile investing in, given that they have promises to reduce poverty, we run a simple financial cost-benefit analysis (for details see Hagos et al., 2008) of the selected AWMTs yielding mixed results.

We collected establishment cost data mainly from secondary sources and data on production cost and crop revenue from the household survey. Establishment and operation and maintenance (O & M) costs, and the assumed life span of these technologies are reported in Table 3 below. Assuming a discount rate of 8 % we calculated a net present values (NPV) of project worth to assess their social and private financial worth16. Assuming that farmers cover all investment, operation & maintenance and production costs, the corresponding net present values (NPV1 in Table 8) of all technologies, except river diversions, are negative even at 5 percent of social discount rate showing that these technologies are not financially viable from social financial cost-benefit analysis perspective. We even calculated NPVs by excluding the opportunity cost of labor (while still investment repayment and O & M costs are accounted for) to see if they become worthwhile of investing, as farmers do usually use family labor and does not involve direct cost (except the forgone income opportunity or leisure time). The calculated values (NPV2) show that only shallow wells and river diversions are financially viable.

Currently, the government, with donor and NGO involvement, is responsible for promoting most of these technologies.

In areas where the ground water potential is found to be high, the government is promoting deep wells by covering the total establishment costs

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16 8 percent is the current banking lending rate for long–term investment loans in Ethiopia (Tesfay, 2008).

while farmers are expected only to cover the operation (e.g. electricity costs) and maintenance costs. River diversions and small dams are also usually provided by the government and farmers are expected to cover operation and maintenance costs. However, in the case of ponds and shallow wells, after initial introduction with strong government support, farmers are expected to cover full cost of establishment. The government promises only technical support to farmers who would like to introduce these technologies besides providing, at cost, valuable water withdrawal and application inputs. This implies that the private cost of accessing these technologies is very low although provided at high social costs. Hence, it is interesting to assess the private financial viability of these technologies by excluding investment costs and only accounting for operation and maintenance costs and production costs.

Instead of the baseline scenarios (NPV1 and VPV2), we estimated NPV values by considering, first, that the opportunity cost of labor and O & M (ruling out investment recovery) in the calculation and latter all investment repayment cost, O & M and opportunity cost of labor are excluded. If opportunity cost of labor and O & M is only considered in the calculation (NPV3), ponds and small dams are not still financially viable while shallow and deep wells and river diversions are financially viable. In this case, unless establishment costs are considered as sunk costs, the financial returns of ponds and small dams, given current production and market conditions, are not promising. In the extreme case where all investment repayment cost, O & M and opportunity cost of labor are excluded (NPV 4), a very unrealistic scenario, all

technologies except ponds become financially viable implying that ponds are not financially viable under any of these circumstances. This needs to be taken into account while making the choice what to invest on.

**Table 8: Cost-benefit estimates of selected water harvesting structures (in ETB/ha or unit)**

| Type of technologies | Establishment costs | Operating cost | Life span (# years) | O & M cost 10% | Production cost ETB/ha | Crop value ETB/ha | NPV 1 ETB /ha | NPV 2 ETB /ha | NPV 3 ETB /ha | NPV 4 ETB /ha |
|---|---|---|---|---|---|---|---|---|---|---|
| Pond | 5980± | - | 10 | 388.8 | 5901.0 | 7861.0 | -28864 | -10354 | -23532 | -5022 |
| Shallow wells | 9343+ | - | 12 | 584.2 | 3531.2 | 4467.0 | -2246 | 8347 | 6083 | 16677 |
| Deep well/ha | 94292♣ | 2500 | 25 | 2841.8 | 2616.2 | 9843.4 | -28082 | -19346 | 56438 | 65174 |
| Small dam/ha | 50000 | - | 25 | 5000 | 2919.4 | 12,070.8 | -47244 | -28918 | -2662 | 15663 |
| River diversion/ha | 50000 | - | 25 | 5000 | 1629.3 | 2867.5 | 53131 | 50999 | 97713 | 95581 |
| Rainfed (reference) | | | | | 1804.0 | 2894.4 | - | | | |

**Source:** Tesfay (2008) and own calculation

± Includes costs of pond construction, geo-membrane plus treadle pump.

+ Includes costs of well construction and for purchase of generator pump.

♣ The cost stream include system installation cost (ETB 53,253.75 per hectare), electricity installation (ETB 2,543 per hectare), construction of generator house (ETB 356 per hectare), and electro mechanical works (ETB 9,722 per hectare).

From social financial cost benefit analysis perspective ponds, deep wells and small dams are not fully financially viable (if investment recovery option is considered); the most important implication of these findings is that, a widespread adoption of these technologies could not be expected without continued government support in proving these technologies. The reverse side of the story is if the government is to institutionalize investment cost recovery schemes, farmers operating particularly deep wells and small dams may not be able to pay unless some thing changes in the profitability of these systems. Hence, it is important to seek ways to improve the performance of these technologies through promotion of profitable cropping patterns and improved marketing conditions. This will have serious implications for poverty reduction and growth, because as a report by AfDB, FAO, IFAD, IWMI, and the World Bank (2007) argued without profitability the necessary income gains cannot be achieved and without profitability there is unlikely to be economic viability. However, there are even reported cases where farmers use ponds successfully (not only the other promising ones) to grow cash crops, and these farmers consider ponds as promising technologies. Exploring under which circumstances the different AWMTs work and what are the determinants of successful adoption of each of these technologies is critical beyond doing simple and dirty cost benefit analysis.

## 6. 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. Moreover, the study aims to assess the financial viability of these technologies and its implication for poverty reduction. 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 incidence 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 found to be technology specific. Accordingly, deep wells, river diversions

and micro dams have led to 50, 32 and 25 percent reduction in poverty incidences compared to the reference, i.e. rain fed system. This may imply that there is a need to promote more micro deep wells, river diversions and small dams 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.

The choice of between these technologies has to be made considering their relative financial viability (from cost-benefits analysis perspective) and poverty reduction impacts compared to other available options that could improve rain fed agriculture. This is especially important because farmers are not made to bear the full investment costs of these technologies as the government is the major provider of these technologies. In this line, assuming that establishment costs are disregarded from the computation, shallow and deep wells and river diversions were found to be financially viable technological options while ponds and small dams were not. Furthermore, given the poverty reduction impacts of ponds and small dams are relatively modest compared to deep wells and diversions, it is important to consider whether they are worthwhile of investment. On the other hand, deep

wells are not also financially viable (if investment recovery option is considered); the most important implication of these findings is that, a widespread adoption of these technologies could not be expected without continued government support in proving these technologies. The reverse side of the story is if the government is to institutionalize investment recovery scheme, farmers operating deep wells and small dams may not be able to pay unless some thing changes in the profitability of these systems. Hence, it is important to seek ways to improve the performance of these technologies through promotion of profitable cropping patterns and improved marketing conditions.

While poverty analysis techniques do not have in-built mechanisms of creating comparable groups, and hence, could lead to attribution bias16, our results from the propensity score matching, however, indicated that the average treatment effect of using 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

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[16] 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.

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 financially viable and resilient to climate change and variability.

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