Kidanemariam G. GEBREHIWOT*, Daniel MAKINA and Thomas WOLDU*****

The impact of micro-irrigation on households' welfare in the northern part of Ethiopia: an endogenous switching regression approach

The paper uses an endogenous switching regression model to measure the impact of participation in micro-irrigation development on households' welfare. The model takes into account selection bias associated with programme participation and endogeneity problems often encountered in most programme evaluations. A total of 482 households (195 irrigation users and 287 non-users) were used to generate all the necessary variables. To capture the impact of the irrigation on household welfare, two indicators were considered, namely household farm income (Y) and household fixed asset formation (F) (evaluated at market price during the survey period). The results show a positive and significant impact of irrigation use on the two outcome variables: income by 8.8 per cent and asset formation by 186 per cent as compared to non-users. This shows how important the micro-irrigation schemes are in improving the welfare of poor farmers in the research areas. Furthermore, the empirical results show that the probability of using one of the water sources (irrigation scheme) is associated with farm experience (age as proxy), farmer-to-farmer contact (the existence of an irrigation user neighbour), family size, the state of credit constraint, the number of visits by extension agents and the cost of irrigation development. As a robustness check, different models were applied and results were found consistent, both qualitatively and quantitatively.

Keywords: micro-irrigation, household farm income, household fixed asset formation

* Mekelle University, P.O. Box 451, Tigrai, Ethiopia. Corresponding author: kidane.gebregziabher@mu.edu.et
** University of South Africa, Pretoria, South Africa.
*** International Food Policy Research Institute, Addis Ababa, Ethiopia.

Introduction

Ethiopia, despite achieving economic growth continuously in excess of 10 per cent per annum in the last decade, is one of the poorest countries in Sub-Saharan Africa (SSA). Poverty is widespread and deep-rooted and constitutes the development priority of the country. About 30 per cent of the population lives below the poverty line (set at USD 1.25 per person per day) (WB, 2013). The challenges that Ethiopia face, in terms of poverty and food insecurity, are associated with both inadequate food production and natural crop failure due to erratic rainfall (Awulachew *et al*., 2007).

In a study conducted to assess the impact of climate change on production at sub-national level for SSA, Liu *et al*. (2008) identified countries such as Ethiopia, Uganda and Rwanda as future drought hotspots. However, less than 4 per cent of renewable water resources in Africa are withdrawn for agriculture. To reverse the current underdeveloped nature of irrigated agriculture in SSA, there is a strong theoretical argument for expanding small-scale irrigation schemes to increase agricultural production in support of economic development and the attainment of food security in the region (de Fraiture and Giordano, 2014). In Ethiopia, special focus has been given since 2003 to household-level water harvesting schemes such as ponds, deep and shallow wells, and river diversions, as an integral part of programmes aimed at breaking the cycle of food insecurity. The aim is to make water available to supplement rainfed agriculture through small-scale irrigation during the critical stage of plant growth when rainfall is inadequate (Hagos *et al*., 2006).

The economic literature on adoption of agricultural technologies (including irrigation) uses various household, farm, social and economic variables to explain the level as well as the intensity of adoption and the impact of these technologies on adopters' welfare. In general it has been found that (a) an increase in the price or cost of technology reduces a farmer's likelihood to adopt (Caswell and Zilberman, 1985; Feder *et al*., 1985); (b) households with larger farms are more likely to adopt (Feder, 1980; Rahm and Huffman, 1984; Putler and Zilberman, 1988); (c) an adopter's human capital endowment variables such as age, gender, education and experience affects the likelihood to adopt (Huffman, 1977; Rahm and Huffman, 1984; Putler and Zilberman, 1988); (d) social capital (membership of social networks) and institutional capital (access to institutional services such as credit and extension service) are also likely to induce farmers to take some risks and adopt technologies.

Several studies have been conducted to assess the impact on household welfare after the adoption of new technologies, including irrigation. In India, access to irrigation has had a positive impact on poverty reduction (Fan *et al*., 1999; Narayanamoorthy, 2001; Shah and Singh, 2002). Gebregziabher *et al*. (2012) found that, in terms of their technical efficiency, irrigator farmers in northern Ethiopia operated on a higher production frontier with significant inefficiencies, while rainfed farms were on a lower production frontier with high efficiency levels. Hussain and Hanjra (2003) showed that irrigation enabled households to improve crop productivity so that they can grow high-value crops that generate higher incomes and employment as well as a higher implicit wage rate for family labour. A comparison between irrigators and non-irrigators in China showed that irrigation contributed to increased yields for almost all crops and higher income for farmers in all areas (Huang *et al*., 2006).

Dillon (2011), using a panel from northern Mali household data, found a positive and significant effect of access to irrigation on household consumption, assets and informal insurance as outcome indicators. Access to irrigation increased household consumption by 27-30 per cent relative to water-recession and rainfed cultivators. Hagos *et al*. (2012), using 1,517 sample households drawn from four regional states of Ethiopia, reported that access to selected agricultural water management technologies had a significant effect on poverty reduction. However, despite the data richness in terms of sample size and geographical representation, the model specification and estimation process did not address the selection bias that could arise between the adoption decision and the outcome equation. Using a household data set from the Tigray region in northern Ethiopia, similar results were reported by Gebregziabher *et al*. (2009). Lipton *et al*. (2003) documented the various ways in which the benefits of irrigation can improve the livelihoods of both irrigators and non-irrigators. These included increased production and income, reduced risk and application of agricultural inputs and additional job creation for rural landless people.

Bhattarai *et al.* (2002) could not establish a straightforward relationship between irrigation and poverty alleviation in selected Asian countries. Similar results were echoed by Berhanu and Pender (2002) who showed the limited impact of irrigation development on input use and farm productivity. Using time series data, Jin *et al*. (2002) could not find a link between irrigation and total factor productivity growth in the major grain producers in China. In a study conducted in Ghana, Burkina Faso and Niger on whether government support for different water management systems has any impact on rice productivity, Katic *et al*. (2013) showed that policy interventions did not significantly enhance the profitability of rice-producing beneficiary farmers. Depending on the nature of the selection problem, if the technology adopters are from the already better off community, the impact will be upward bias, and vice versa.

Most of these studies have relied on income and/or consumption to measure poverty (flow variable) and did not address the selection bias problem between the adoption process and the second stage outcome equation. In this paper, we assess the impact of the micro-irrigation[1] project on household welfare in the Tigray region of northern Ethiopia. We endeavour to address the self-selection bias by using a relatively more robust model and, to address the measurement error, we tried to use alternative welfare indicators, income (flow) and fixed asset holding (stock), to measure the welfare implication of irrigation adoption.

Methodology

Study area

The study was conducted in three districts of the Tigray region. The climate of Tigray is broadly arid and semi-arid, with around nine or ten dry months and rainfall concentrated during July and August. Most parts of the region experience very erratic and inadequate rainfall (even during the two rainy months) that is precarious for crop production (Hagos *et al*., 2006). Moreover, the region encounters severe drought almost every five years. Despite all these challenges, during 'normal' rainy seasons (i.e. when drought does not occur) the region has an annual runoff of around 9 billion m^3 and can irrigate its potential irrigable area of 300,000 ha (Awulachew *et al*., 2007). However, the developed irrigable land of the region currently does not exceed 75,000 ha. The three districts used in this study were selected because they are known to have both rainfed farming and micro-irrigation schemes such as ponds, wells and river diversions. Moreover, these districts have irrigation users and non-users sharing the same natural and agro-climatic conditions. Except for some small areas which practice dry season cultivation using micro-irrigation, rainfed agriculture predominates which involves the cultivation of wheat, teff (*Eragrostis tef*), maize, oilseeds and pulses. Both exotic and indigenous vegetables and crops are irrigated and these include onions, tomatoes, pepper, garlic and maize.

Study design and data

A survey of 482 farmers comprising 287 non-users and 195 users of the different irrigation schemes was conducted in March 2012. In obtaining the sample for the survey, a multistage sampling technique was used. Firstly, three districts with good distribution of different irrigation schemes were sampled purposefully. In the second stage, five sub-districts were randomly selected. Thirdly, using extension workers' lists, farmers in each sub-district were stratified into two groups, namely irrigators (river diversion, wells and ponds) and non-irrigators (rainfed farmers). A questionnaire was used to gather data on households' income and asset holdings, household characteristics, and farm characteristics from both users and non-users, and sub-district level information.

Model specification

Microeconomic evaluations of the impact of an intervention (for instance, irrigation use) on the final outcome (household welfare) were based on the model developed by Becker (1964) and Mincer (1974). However, the decision to adopt new technology, in our case, irrigation scheme, is voluntary; the familiar problem of sample selection bias may result: farmers who use irrigation are also likely to be the ones who find it most profitable (Fuglie and Bosch, 1995). For example, farmers who are more wealthy and productive are more likely to be those who use irrigation. Hence, the self-selection into irrigation scheme utilisation would be the source of endogeneity, and failure to account for this will overstate the true impact of irrigation (Alene and Manyong, 2007).

Lee (1978) developed an approach for estimating models of this type which he called endogenous switching regression (ESR). In this approach, the decision is modelled by standard limited dependent variable models, and the second stage outcome variables are then estimated separately for each group (irrigation users and non-users), conditional on having made the decision. Let the decision to use one of the micro-irrigation schemes be a dichotomous choice, where a farmer decides to have irrigation when there is a positive perceived difference between using the scheme and not having the scheme.

Let this difference be denoted as I^* so that $I^*>0$ corresponds to the net benefit of having the scheme exceeding that

[1] Micro-irrigation is the slow application of water on, above, or below the soil by surface drip, subsurface drip, bubbler and micro-sprinkler systems. Water is applied as discrete or continuous drips, tiny streams or miniature spray through emitters or applicators placed along a water delivery line adjacent to the plant row (Lamm *et al.*, 2007).

of not using the scheme, and it is under this condition that the farmer decides to use the scheme. However, I^* is not observable; what is observed is I, which represents the observed farmer's decision choice. The expected utility of having an irrigation scheme, I_1^* (adopters or regime 1) compared to the utility of not having, I_0^* (non-adopters or regime 2), and the decision to own irrigation occurs if $I_1^* > I_0^*$. Based on Lokshin and Sajaia (2004), the relationship can be expressed as:

$$I = 1 \text{ if } \alpha Z'_i + U_i, \text{ if } I^* > 0$$
$$I = 0 \text{ if } \alpha Z'_i + U_i, \text{ if } I^* < 0 \quad (1)$$

$$Regime\ 1: \ln W_{1i} = \left.\begin{matrix}\ln Y_{1i} \\ \ln F_{1i}\end{matrix}\right\} = X\beta_1 + \varepsilon_1 \, ; \, if \ I = 1 \quad (2)$$

$$Regime\ 2: \ln W_{2i} = \left.\begin{matrix}\ln Y_{2i} \\ \ln F_{2i}\end{matrix}\right\} = X\beta_2 + \varepsilon_2 \, ; \, if \ I = 0 \quad (3)$$

where Z is a vector of explanatory variables (which includes household and farm characteristics; social and institutional variables); α is a vector of unknown parameters to be estimated; and U_i is a random error term and factors not observed by the researcher but known to the household, with mean zero and variance σ_U^2 (Alene and Manyong, 2007). $\ln W_{1i}$ and $\ln W_{2i}$ are the natural logs of welfare indicators (outcome variables) for regime 1 and regime 2 respectively. Welfare is captured by household income (Y) and fixed assets (F); where $\ln Y_{1i}$ and $\ln F_{1i}$ represent natural logs of income and fixed assets for adopters, $\ln Y_{2i}$ and $\ln F_{2i}$ are natural logs of income and fixed assets for non-adopters. ε_1 and ε_2 are error terms for regime 1 and 2 functions respectively.

Since the first stage decision variable I (to have an irrigation scheme) is endogenous, OLS estimates in equations (2) and (3) will suffer from sample selection bias, namely the error terms in equations (2) and (3), conditional on the sample selection criteria, have non-zero expected values (Lee, 1978; Maddala, 1983; Fuglie and Bosch, 1995). Lee (1978) treats sample selection as a missing-variable problem. For identification purposes, and to satisfy the usual order condition, Z_i contained one variable (whether household has a neighbour/s or not) not in X_i so as to impose an exclusion restriction on equations (2) and (3). Having a neighbour who adopts any modern technology may help fellow farmers to observe, learn and, if they become convinced of the benefits, eventually adopt the technology; thus technology diffusion will continue. In our situation, the presence of a neighbour who adopts one of the irrigation schemes is expected to affect the decision to adopt or not, but not the welfare status (income and asset holdings of a household). Hence, the *IrrigationUserN* neighbour adopter variable is used as an instrumental variable. In developing countries, social networks such as neighbours, friends and families are the main sources of information and confidence in the process of technology or new practice adoption. Hence, the existence of a neighbour adopter (farmer-to-farmer) is expected to influence peer fellow neighbours to adopt one of the irrigation schemes, but not the income and asset holdings of households. Moreover, OLS estimates do not explicitly account for potential production function differences between households with irrigation and rainfed farmers. Hence, the variable whether a household has a neighbour/s or not is used as an instrument (identification variable). Assuming U_i, ε_2 and ε_1 to have a trivariate normal distribution with mean vector zero and covariance matrix will have the following variance-covariance structure:

$$\operatorname{cov}(\varepsilon_1, \varepsilon_2, U_i) = \begin{bmatrix} \sigma_U^2 & \sigma_{1U} & \sigma_{2U} \\ \sigma_{1U} & \sigma_1^2 & \cdot \\ \sigma_{2U} & \cdot & \sigma_2^2 \end{bmatrix} \quad (4)$$

where $\operatorname{var}(\varepsilon_1) = \sigma_1^2$, $\operatorname{var}(\varepsilon_2) = \sigma_2^2$ and $\operatorname{var}(U_i) = \sigma_U^2$, and $\operatorname{cov}(\varepsilon_1, U_i) = \sigma_{1U}$, $\operatorname{cov}(\varepsilon_2, U_i) = \sigma_{2U}$. The covariance between ε_2, and U_i is not defined, as Y_2 and Y_1 are never observed simultaneously (Lokshin and Sajaia, 2004). Since probit maximum likelihood is used to estimate α, it is estimable only up to a scalar factor and hence it can be assumed that $\sigma_U^2 = 1$ (Maddala, 1983). Given the assumption with respect to the distribution of the disturbance terms, the logarithmic likelihood function for the system of (2 and 3) is:

$$\ln L = \sum_i (I_i w_i [\ln\{F(\eta_{1i})\} + \ln\{(\varepsilon_{1i}/\sigma_1)/\sigma_1\}] +$$
$$(1 - I_i) w_i [\ln\{1 - F(\eta_{2i})\} + \ln\{f(\varepsilon_{2i}/\sigma_2)/\sigma_2\}]) \quad (5)$$

where F is a cumulative normal distribution function, f is a normal density function, w_i is an optimal weight for observation i and

$$\eta_{ji} = \frac{(\gamma Z_i + \rho_j \varepsilon_{ji}/\sigma_j)}{\sqrt{1 - \rho_j^2}} \text{ where } j = 1, 2$$

where $\rho_1 = \dfrac{\sigma_{1U}^2}{\sigma_U \sigma_1}$ is the correlation coefficient between ε_{1i} and U_i and $\rho_2 = \dfrac{\sigma_{2U}^2}{\sigma_U \sigma_2}$ is the correlation coefficient between ε_{2i} and U_i.

After estimating the model's parameters, the following conditional (the focus of analysis) and unconditional expectations could be calculated:

Unconditional expectations:

$$E(\ln W_{1i} \mid x_{1i}) = x_{1i}\beta_1 \quad (6)$$

$$E(\ln W_{2i} \mid x_{2i}) = x_{2i}\beta_2 \quad (7)$$

Conditional expectations:

$$E(\ln W_{1i} \mid I = 1, x_{1i}) = x_{1i}\beta_1 + \sigma_1 \rho_1 f(\gamma Z_i)/F(\gamma Z_i) \quad (8)$$

$$E(\ln W_{1i} \mid I = 0, x_{1i}) = x_{1i}\beta_1 - \sigma_1 \rho_1 f(\gamma Z_i)/\{1 - F(\gamma Z_i)\} \quad (9)$$

$$E(\ln W_{2i} \mid I = 1, x_{2i}) = x_{2i}\beta_2 + \sigma_2 \rho_2 f(\gamma Z_i)/F(\gamma Z_i) \quad (10)$$

$$E(\ln W_{2i} \mid I = 0, x_{2i}) = x_{2i}\beta_2 - \sigma_2 \rho_2 f(\gamma Z_i)/\{1 - F(\gamma Z_i)\} \quad (11)$$

Given the above formulation, the following can be calculated and compared:

- The effect of adoption on adopters (treatment effect on the treated – *TT*) as the difference between equations (8) and (10), which represents the effect of having irrigation on the two welfare indicators:

$$TT = E(\ln W_{1i} \mid I = 1, x_{1i}) - E(\ln W_{2i} \mid I = 1, x_{2i}) \quad (12)$$

- The effect of adoption on non-adopters (treatment on the untreated $-TU$) as the difference between equations (11) and (9):

$$TU = E(\ln W_{2i} \mid I = 0, x_{2i}) - E(\ln W_{1i} \mid I = 0, x_{1i}) \quad (13)$$

- The policy-relevant treatment effects can also be differentiated from the heterogeneity effect. For example, farm households that adopted micro-irrigation may have achieved a higher level of welfare (measured by the selected two welfare indicators) than farm households that did not adopt although they decided to adopt; because of unobservable characteristics such as their risk-taking behaviour. Following Carter and Milon (2005), 'the effect of base heterogeneity' (BH_N) is defined for the group of farm households that decided to adopt as the difference between equations (8) and (9):

$$BH_N = E(\ln W_{1i} \mid I = 1, x_{1i}) - E(\ln W_{1i} \mid I = 0, x_{1i}) \quad (14)$$

- The second type of base heterogeneity (BH_2) can be calculated for the group of farm households that decided not to adopt as the difference between equations (10) and (11):

$$BH_2 = E(\ln W_{2i} \mid I = 1, x_{2i}) - E(\ln W_{2i} \mid I = 0, x_{2i}) \quad (15)$$

- The third type of heterogeneity is the 'transitional heterogeneity' (TH), that is whether the impact of having micro-irrigation is larger or smaller for the farm households that owned or for the farm household that did not own in the counterfactual case that they did own, that is the difference between equations (12) and (13), i.e. (TT) minus (TU):

$$TH = TT - TU = [E(\ln W_{1i} \mid I = 1, x_{1i}) - E(\ln W_{2i} \mid I = 1, x_{2i})] - [E(\ln W_{2i} \mid I = 0, x_{2i}) - E(\ln W_{1i} \mid I = 0, x_{1i})] \quad (16)$$

The switching regression model accounts for both endogeneity of technology adoption and possible sample selection, and allows the different household and farm characteristic variables to play differential roles, both in terms of qualitative and quantitative effects on the respective varietal technologies (Fuglie and Bosch 1995; Alene and Manyong, 2007). To our knowledge, no study has explicitly accounted for underlying technological differences among farmers in assessing the effects of irrigation on the impact of household welfare.

Results and discussion

Descriptive results

Seventy-nine per cent of irrigator households are headed by males, compared to 71 per cent of non-irrigators (Table 1). In terms of literacy status, 32 per cent of irrigator household heads are literate compared to 26.7 per cent of non-irrigators. On average, irrigation adopters have a 9 per cent bigger family size than non-adopters. The overall picture indicates that the irrigators have better quality and quantity of labour that might have helped them to engage in labour and capital-intensive activities.

Non-users are located far away from a development extension office. Moreover, users are more connected to various social networks where they can get information, which might have helped them to use the irrigation service. There was a significant difference between irrigators and non-irrigators in credit utilisation. Approximately 63 per cent of irrigators had applied for credit and 58 per cent of them had access to credit service, while the corresponding figures for non-irrigators were 57 per cent and 51 per cent respectively.

Table 1: Household-, farm- and village-level characteristics of irrigators and non-irrigators surveyed in the research.

Variable	Variable definition	Irrigators		Non-irrigators		t-test
		Mean	SD	Mean	SD	
Welfare indicators						
Ln Y	Log transformed crop income (ETB)	2825.84	141.85	2534.3	101.8	-1.66**
Ln F	Log transformed per capita total asset value (ETB)	702.94	57.62	503.26	92.44	-1.84**
Household characteristics						
Headgender	Household head gender (1 = male and 0 otherwise)	0.79	0.02	0.7118	0.03	-2.21**
Lnheadage	Log transformed age of the household head (in years)	52.89	0.84	52.95	0.88	0.054
HHedu	Household head literacy status: dummy (1 = literate and 0 otherwise)	0.32	0.03	0.27	0.03	-1.51*
Familysize	Family size (number)	5.93	0.14	5.46	0.14	-2.33***
Adultequivalent	Family size (adult equivalent)	4.33	0.10	4.04	0.10	-1.98**
tryloan	Access to credit (if the household is credit constrained = 1, 0 otherwise)	0.51	0.03	0.52	0.04	-0.23
Farm and village characteristics						
Lnplotsize	Log transformed farm size (tsemad; 1 ha = 4 tsemad)	2.85	0.10	2.28	0.08	-4.43***
IrrigationUserNgb	If the household had an adopter neighbour prior to his adoption (yes = 1, 0 otherwise)	0.85	0.02	0.37	0.03	-13.59***
Tabiacode	Village dummy 1 = Adiqsanded; 2 = Genfel; 3 = Tsenkanet; 4 = D.Birhan; 5 = my-Kado					
Number_visits_EA	Visits by extension agents (number)	5.83	0.57	3.25	0.282	-4.48***
Lncost	Average cost per irrigation scheme (ETB)	2.46	3.4	-		
howmnysnw	In social network associations (number)	1.4	0.07	1.29	0.05	-1.365

Source: own calculations

On average, irrigators had a 25 per cent larger plot size than non-irrigators, suggesting a clear wealth difference.

There are statistically significant differences between the two groups with respect to household income and total asset holdings. The per capita asset holding was about ETB[2] 621 for irrigators, whereas for non-irrigators it was approximately ETB 361. The mean per capita consumption expenditure for irrigators was ETB 1,880 per annum, while the corresponding figure for non-irrigators was ETB 1,748. Finally, the per capita income of households using irrigation was ETB 1,473, which was approximately 37 per cent higher than that of non-irrigators. On other hand, non-irrigators had higher off-farm participation (97 per cent) than irrigators (95 per cent). With regard to off-farm income, irrigators derive slightly higher income (ETB 2,360) than non-irrigators (ETB 2,069)[3].

Econometric results

Factors affecting adoption of irrigation

The adoption of an irrigation scheme and its outcome for household welfare in terms of household income and asset formation can be modelled as a two-stage framework. In the first stage, a selection model for irrigation adoption was estimated using probit and, in the second stage, the household welfare outcome was estimated with equations using different models. The model diagnostic statistics (Table 2) show goodness-of-fit measures that indicate that the estimated models fit the data reasonably well. Likelihood ratio tests show that the parameter estimates are statistically significantly different from zero at less than one per cent significance level. The model correctly predicts 92.5 per cent of the cases; and the pseudo R-squared measure of 0.70 is also reasonably high, given the cross-sectional nature of our data.

The analysis of the probit regression shows that seven of the 11 explanatory variables are significant and most of them have the expected sign, except adult labour force, due to its high correlation with family size, and cost of irrigation, which is only observed for irrigation users. The significant variables include: neighbour irrigation user (IrrigationUserN), credit constraint (tryloan), head age (lnHeadage), family size (lnFamily_size), cost of irrigation scheme, and number of visits by extension agent (Number_visits_EA).

The parameter estimates of the probit model provide only the direction of the effect of the independent variables on the dependent (response) variable: estimates do not represent the actual magnitude of change or probabilities. Thus, the marginal effects from the probit, which measures the probability of being an irrigation user with respect to a unit change in an independent variable, was calculated using the mfx stata command.

The relationship between technology adoption and household age (Headage) has remained mixed. This result is in line with the published literature. Lapar and Pandey (1999), for adoption decisions of soil conservation in the Philippines uplands, Baidu-Forson (1999), regarding the adoption of land-enhancing technology in the Sahel; Fufa and Hassan (2006) and Chirwa (2005), in terms of fertiliser adoption in Ethiopia and hybrid seed for Malawi respectively, found negative relationships. This implies that, as farmers grow older, they become more risk averse and less willing to adopt new farming technologies. On the other hand, Polson and Spencer (1991) and Abay and Admassie (2004) found positive relationships between age and improved cassava variety adoption in Nigeria and chemical fertiliser adoption in Ethiopia respectively. Age when taken as proxy for farm experience (human capital theory) will be positive; but older farmers with a very short planning horizon and high risk averse age can be negatively associated with technology adoption (Zepeda, 1990). Hence, the sign of the household head age is very difficult to predict a priori.

The family size variable was significant (at the 5 per cent level) and positive. This is again consistent with our expectation. Developing an irrigation scheme as well as irrigable fields requires high labour input, and, in view of imperfect labour market, farmers are dependent on their family labour.

Contact with extension services gives farmers greater access to information on technology, via communications and more opportunities to participate in demonstration tests. Accordingly, access to extension services (captured by the number of visits by an extension agent) showed a positive and significant effect. The result is consistent with our expectations and the findings of Gebrehiwot (2017) who found a positive relationship between extension service and farmers' technical efficiency in the northern part of Ethiopia.

Credit is very important in that it helps farmers to acquire all the necessary inputs in the right quantities and qualities at the right time. However, when are farmers are credit constrained, consistent with our expectation, they were among the non-adopters and this result was statistically significant. Similar results were also reported by He *et al*. (2007) and Deressa *et al*. (2009).

Finally, having access to farmer-to-farmer extension (the existence of a neighbour adopter) increased the likelihood of using one of the irrigation schemes by 41 per cent, consistent with our expectation. Similar results were reported by Deressa *et al* (2009).

Table 2: Probit model estimates of adoption of irrigation schemes (Irrigation_user): marginal effects.

Variable	Marginal effects (dy/dx)
Lnheadage	5.924 (3.373)*
$Lnheadage^2$	-10.967 (3.373)*
Headgender	0.071 (0.098)
HHedu	0.037 (0.013)***
Familysize	0.107 (0.054)**
Adultequivalent	-0.126 (0.072)*
Lnplotsize	-0.097 (0.108)
IrrigationUserN	0.430 (0.067)***
Number_visits_EA	0.185 (0.086)**
tryloan	-0.150 (0.085)*
Lncost of irrigation	0.186 (0.019)***
Wald ($\chi^2_{0.99}$ = 11) df=186.65 Prob.>chi^2=0.0000	
Percentage of correct predictions	
Irrigation_user (I=1)	97.5%
Irrigation_user (I=0)	91.5%
Overall correctly classified	93.5%
Pseudo R^2	0.71

*, ** and *** represent significance at 0.1, 0.05, and 0.01 levels respectively
Source: own calculations

[2] Ethiopian Birr; USD 1=approximately ETB 17.12 at the time the study was conducted.
[3] Data available from the corresponding author upon request.

Welfare estimation results

The ESR model was estimated by an efficient method of full information maximum likelihood (Lokshin and Sajaia, 2004), as compared to the alternative two-step procedure proposed by Madalla (1983). The estimated coefficient of correlation between the irrigation adoption decision and the household income (ρ_{1cY}) for regime 1 and household asset formation (ρ_{2cF}) for regime 2 are statistically different from zero (Table 3). The results suggest that both observed and unobserved factors influence the participation in irrigation and welfare outcomes. The significance of the coefficient of correlation between the first stage equation and the welfare equation indicates that self-selection occurred in the participation of irrigation schemes. The differences in the household income and asset formation equation coefficients between the farm households of those participating in irrigation schemes and those not participating illustrate the presence of heterogeneity in the sample.

An important question is whether farm households that adopted the different irrigation schemes gained benefits in terms of household income and fixed asset formation (estimating impact of adoption). The results, obtained using equations (12)-(16), are presented in Table 4. The observed difference in income and fixed asset formation between households who adopt and do not adopt was 0.145 ((a)-(b) in Table 4) and 0.898 ((e)-(f) in Table 4) respectively. However, this simple comparison is misleading because it does not account for other unobserved factors that may have impacted the two outcome variables (households' income and fixed asset formation).

Hence, to account for the potential unobservable effect on the outcome variable column [3] is included which adjusts the 'base heterogeneity'[4] and gives the differences in expected household income and value fixed asset formation (Carter and Milon, 2005). With the counterfactual condition that, the adopters placed in the non-adopters status BH_{1Y} and BH_{1F} in Table 4; the households would be expected to earn 0.346 points less income and to own 0.814 points less fixed assets on average. Similarly, with the counterfactual condition that the non-adopter households adopt irrigation BH_{0Y} and BH_{0F} in Table 4 and equation (15), the households would earn more income (0.061) but own less asset (-0.053). Under both counterfactual conditions, irrigation using households perform better (with the exception of BH_{2F}) than non-irrigation using households. These differences reflect systematic sources of variation between the two groups that could not be fully captured by the observable variables in the model specifications. Information regarding adoption status alone does not explain households' performance in the two outcome indicators (Y-income and F-fixed asset formation).

Table 4 column [3] presents the treatment effects of irrigation adoption as expected change in income and fixed asset value for a randomly-selected household in each group. For the household group with access to irrigation, the first entry in column [3] measures that the mean effect of access to irrigation (*TT* in equation (12)) was an increase of 0.084 point in income and 1.051 point in fixed asset formation. Since our outcome variables are expressed in natural logarithm it represents 8.8 per cent for income and 186 per cent for asset formation. This implies that participation in the micro-irrigation programme has a positive effect on household welfare in the research area. Similarly, the households without access

[4] For the definition of the different heterogeneity (base and transitional) see equations (14)-(16).

Table 3: Full information maximum likelihood estimates of the switching regression model.

	Ln Y R 1	Ln Y R 2	Ln F R 1	Ln F R 2
tryloan	-0.012 (0.09)	0.176** (0.07)	-0.056 (0.22)	0.316* (0.19)
headgender	0.353** (0.14)	0.406*** (0.08)	0.995*** (0.32)	0.895*** (0.23)
lnheadage	-0.546*** (0.17)	-0.860*** (0.12)	-1.234*** (0.40)	-0.960*** (0.33)
Adultequivalent	0.103*** (0.03)	0.055** (0.02)	-0.160** (0.07)	-0.153** (0.06)
lnplotsize	0.624*** (0.13)	0.691*** (0.09)	0.565* (0.29)	0.247 (0.25)
HHedu	-0.005 (0.02)	0.016 (0.01)	0.085** (0.03)	0.012 (0.03)
howmnysnw	0.160 (0.12)	-0.117 (0.09)	0.033 (0.26)	0.033 (0.24)
_Itabiacode_2	0.266* (0.16)	-0.373*** (0.11)	-0.328 (0.36)	-0.553 (0.29)
_Itabiacode_3	0.148 (0.17)	-0.126 (0.11)	0.082 (0.39)	0.184 (0.28)
_Itabiacode_4	-0.140 (0.15)	0.031 (0.11)	-0.719** (0.35)	-0.269 (0.28)
_Itabiacode_5	0.019 (0.15)	-0.332*** (0.12)	-0.175 (0.36)	0.061 (0.30)
$\rho_{1cY/F}$	-0.367** (0.17)		0.096 (0.19)	
$\rho_{2cY/F}$		-0.176 (0.14)		-0.306** (0.13)

Dependent variables: ln *Y*; and ln *F* for regime 1 and regime 2
*, ** and *** represent significance at 0.1, 0.05, and 0.01 levels respectively
Source: own survey

Table 4: Expected income and asset level and treatment effects.

Sub-sample	Decisions stage		Treatment effect	PSM	OLS		
	Irrigation user [1]	Non-irrigation user [2]	[3]	ATT [4]	Irrigation user [5]	Non-irrigation user [6]	Difference [7]
Ln Y							
Irrigation user	(a) 8.723	(c) 8.639	0.084***				
Non-irrigation user	(d) 8.375	(b) 8.578	-0.203***				
Heterogeneity effects	BH_{1Y}=0.348	BH_{2Y}=0.061	0.287	0.23**	8.62**	8.41***	0.25
Ln F							
Adopters	(e) 7.170	(g) 6.119	1.051***				
Non-adopters	(h) 6.356	(f) 6.172	0.184***				
Heterogeneity effects	BH_{1F}=0.814	BH_{2F}=-0.053	0.867	0.48***	7.09***	6.45**	0.64

Source: own calculations

to irrigation were placed into the status of with access (*TU* in equation (13)); the implication would be a mean decrease in income (0.203 points) and increase in fixed asset formation (0.184 points). Access to irrigation effects is larger for irrigation user households, resulting in a positive value for the transitional heterogeneity effect (equation (16), Table 4). The estimated treatment effects portray that, except in one case, access to irrigation places households in a better welfare position (income and fixed asset value level).

To check the robustness of our results, we estimate alternative models with different model specifications and distributional assumptions: propensity score matching (PSM) and OLS for each regime (Table 4). The results were very similar qualitatively but with lower coefficients. This could arise from differences in estimation efficiencies between ESR on the one hand and PSM and OLS on the other hand. The PSM, which estimates based on observables and does not provide consistent estimation of causal effects in the presence of hidden bias, might result in slightly downward estimates for PSM and OLS.

Summary and conclusions

To measure the impact of participation in micro-irrigation development on households' welfare we used an ESR model, which considers selection bias associated with endogeneity of programme participation as well as self-selection often encountered in most programme evaluations. A total of 482 households (195 participants and 287 non-participants) were used to generate the necessary variables. The first stage decision (whether to use one of the irrigation schemes) was estimated using household and farm characteristics covariates. Among the variables which were statistically significant and have some policy relevance are farmer-to-farmer extension service (neighbour irrigation user) and credit constraints. Hence, given the positive influence of farmer-to-farmer to disseminate information, government should encourage and support farmers' networks, in addition to the conventional extension worker-led extension system. Moreover, to encourage the use of irrigation facilities and thereby improve the income and asset position of rural households, the liquidity constraint should be addressed sustainably, through the provision of micro-credit services.

To capture the impact of the participation on household welfare, two indicators were considered, namely household farm income and household fixed asset formation (evaluated at market price during the survey period). The results show that estimated coefficients of correlation between the irrigation adoption equation and the outcome equations (income and asset formation) were statistically significant. This implies that bias would have resulted in the welfare function had it been estimated without correcting for selection bias associated with programme participation in the study.

Furthermore, the empirical results show that the probability of participating in the irrigation programme is associated with farm experience (age as proxy), household level of education, family size and labour force availability in the household, credit constraint and cost of irrigation development. After controlling the selection bias in the estimation process, the different model estimated results showed that participation in the irrigation programme had increased household welfare of participants: income by 8.8 per cent and fixed asset formation by 186 per cent as compared to non-participants. Given this, we suggest that the government of the Tigray region should extend its support (through extension, access to road and marketing information and credit schemes) so as to increase access to micro-irrigation schemes to other parts of the region and to areas with good ground water potential.

Acknowledgements

The authors wish to express their profound gratitude to VLIR-UOS (Belgium) for the full and generous financial support for this study through the MU-IUC programme. He also sincerely appreciates and recognises the support provided by Mesfin Tilahun and Atsede Gidey during the field survey and all the research site farmers who sat patiently for hours to answer the detailed interviews and the enumerators who worked tirelessly to collect the data are also sincerely thanked.

References

Abay, A. and Assefa, A. (2004): The role of education on the adoption of chemical fertiliser under different socioeconomic environments in Ethiopia. Agricultural Economics **30** (3), 215-228. https://doi.org/10.1111/j.1574-0862.2004.tb00190.x

Adeoti, A.I. (2009): Factors Influencing Irrigation Technology Adoption and Its Impact on Household Poverty in Ghana. Journal of Agriculture and Rural Development in the Tropics and Subtropics **109** (1), 51-63.

Alene, A.D. and Manyong, V.M. (2007): The effects of education on agricultural productivity under traditional and improved technology in northern Nigeria: an endogenous switching regression analysis. Empirical Economics **32** (1), 141-159. https://doi.org/10.1007/s00181-006-0076-3

Awulachew, S.B., Yilma, A.D., Loulseged, M., Loiskandl, W., Ayana, M. and Alamirew, T. (2007): Water Resources and Irrigation Development in Ethiopia. Working Paper 123. Colombo, Sri Lanka: International Water Management Institute.

Baidu-Forson, J. (1999): Factors influencing adoption of land-enhancing technology in the Sahel: lessons from a case study in Niger. Agricultural Economics **20** (3), 231-239. https://doi.org/10.1016/S0169-5150(99)00009-2

Becker, G. (1964): Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education. New York NY: Columbia University Press.

Berhanu, G. and Pender, J. (2002): Policies and institutions to enhance the impact of irrigation development in crop-livestock mixed systems. Paper presented at the International Workshop on Integrated Water and Land Management Research and Capacity Building, Addis Ababa, Ethiopia, 2-4 December 2002.

Bhattarai, M., Sakthivadive, R. and Hussain, I. (2002): Irrigation Impact on Income Inequality and Poverty Alleviation: Policy Issues and Options for Improved Management of Irrigation Systems. Colombo, Sri Lanka: International Water Management Institute.

Carter, D.W. and Milon, J.W. (2005): Price Knowledge in Household Demand for Utility Services. Land Economics **81** (2), 265-283. https://doi.org/10.3368/le.81.2.265

Caswell, M. and Zilberman, D. (1985): The Choices of Irrigation Technologies in California. American Journal of Agricultural

Economics **67**, 224-234. https://doi.org/10.2307/1240673

Chirwa, E.W. (2005): Adoption of fertiliser and hybrid seeds by smallholder maize farmers in Southern Malawi. Development Southern Africa **22** (1), 1-12. https://doi.org/10.1080/03768350500044065

de Fraiturea, C. and Giordano, M. (2014): Small private irrigation: A thriving but overlooked sector. Agricultural Water Management **131**, 167-174. https://doi.org/10.1016/j.agwat.2013.07.005

Deressa, T.T., Hassan, R.M., Ringler, C., Alemu, T. and Yesuf, M. (2009): Determinants of farmers' choice of adaptation methods to climate change in the Nile Basin of Ethiopia. Global Environmental Change **19**, 248-255. https://doi.org/10.1016/j.gloenvcha.2009.01.002

Dillon, A. (2011): The Effect of Irrigation on Poverty Reduction, Asset Accumulation, and Informal Insurance: Evidence from Northern Mali. World Development **39** (12), 2165-2175. https://doi.org/10.1016/j.worlddev.2011.04.006

Fan, S., Hazel, P. and Sukhadeo, T. (1999): Linkages between Government Spending, Growth, and Poverty in Rural India. Research Report No 110. Washington DC: IFPRI.

Feder, G. (1980): Farm Size, Risk Aversion and the Adoption of New Technology under Uncertainty. Oxford Economic Papers **32** (2), 263-283. https://doi.org/10.1093/oxfordjournals.oep.a041479

Feder, G., Just, R.E. and Zilberman, D. (1985): Adoption of Agricultural Innovations in Developing Countries, A Survey. Economic Development and Cultural Change **33**, 255-298. https://doi.org/10.1086/451461

Hagos, F., Gayathri, J., Seleshi, B.A., Mekonnen, L. and Aster, D.Y. (2012): Agricultural water management and poverty in Ethiopia. Agricultural Economics **42** (supplement), 99-111. https://doi.org/10.1111/j.1574-0862.2012.00623.x

Fuglie, K.O and Bosch, D.J. (1995): Economic and Environmental Implications of Soil Nitrogen Testing: A Switching-Regression Analysis. American Journal of Agricultural Economics **77** (4), 891-900. https://doi.org/10.2307/1243812

Fufa, B. and Hassan, R.M. (2006): Determinants of fertilizer use on maize in Eastern Ethiopia: A weighted endogenous sampling analysis of the extent and intensity of adoption. Agrekon **45** (1), 38-49. https://doi.org/10.1080/03031853.2006.9523732

Gebregziabher, G., Namara, R.E. and Holden, S. (2009): Poverty Reduction with irrigation investment: an empirical case study from Tigray, Ethiopia. Agricultural Water Management **96**, 1837-1843. https://doi.org/10.1016/j.agwat.2009.08.004

Gebregziabher, G., Namara, R.E. and Holden, S. (2012): Technical Efficiency of Irrigated and Rain-Fed Smallholder Agriculture in Tigray, Ethiopia: A Comparative Stochastic Frontier Production Function Analysis. Quarterly Journal of International Agriculture **51** (3), 203-226.

Gebrehiwot, K.G. (2017): The impact of agricultural extension on farmers' technical efficiencies in Ethiopia: A stochastic production frontier approach. South African Journal of Economic and Management Sciences **20** (1), a1349. https://doi.org/10.4102/sajems.v20i1.1349

Hagos, F., Kruseman, G., Abreha, Z., Linderhof, V., Mulugeta, A. and Gebresamuel, G. (2006): Impact of small scale water harvesting on household poverty: evidence from northern Ethiopia. PREM Working Paper 07/01. Amsterdam: Vrije Universitiet.

He, X.-F., Cao, H. and Li, F.-M. (2007): Econometric analysis of the determinants of adoption of rainwater harvesting and supplementary irrigation technology (RHSIT) in the semiarid Loess Plateau of China. Agricultural Water Management **89**, 243-250. https://doi.org/10.1016/j.agwat.2007.01.006

Huang, Q., Rozelle, S., Lohmar, B., Huang, J. and Wang, J. (2006): Irrigation, agricultural performance and poverty reduction in China. Food Policy **31**, 30-52. https://doi.org/10.1016/j.foodpol.2005.06.004

Huffman, W.E. (1977): Allocative Efficiency: The Role of Human Capital. Quarterly Journal of Economics **91**, 59-79. https://doi.org/10.2307/1883138

Hussain, I. and Hanjra, M. (2003): Does irrigation water matter for rural poverty alleviation? Evidence from South and South-East Asia. Water Policy **5**, 429-442.

Jin, S., Huang, J., Hu, R. and Rozelle, S. (2002): The creation and spread of technology and total factor productivity in China's agriculture. American Journal of Agricultural Economics **84** (4), 916-930. https://doi.org/10.1111/1467-8276.00043

Katic, P.G., Regassa, E., Namara, R.E., Hope, L., Owusu, E. and Fujii, H. (2013): Water Resources and Economics **1**, 75-92. https://doi.org/10.1016/j.wre.2013.03.001

Lamm, F.R., Ayars, J.E. and Nakayama, F.S. (eds) (2007): Microirrigation for crop production: design, operation and management. Developments in Agricultural Engineering 13. Amsterdam: Elsevier.

Lapar, M.L.A. and Pandey, S. (1999): Adoption of soil conservation: the case of the Philippines uplands. Agricultural Economics **21** (3), 241-256. https://doi.org/10.1016/S0169-5150(99)00028-6

Lee, L.F. (1978): Unionism and Wage Rates: A Simultaneous Equations Model with Qualitative and Limited Dependent Variables. International Economic Review **19** (2), 415-433. https://doi.org/10.2307/2526310

Lipton, M., Litchfield, J. and Figures, J.M. (2003): The effects of irrigation on poverty: a framework for analysis. Water Policy **5** (6), 413-427.

Liu, J., Fritz, S., van Wesenbeeck, C.F.A., Fuchs, M., You, L., Obersteiner, M. and Yang, H. (2008): A spatially explicit assessment of current and future hotspots of hunger in Sub-Saharan Africa in the context of global change. Global and Planetary Change **64**, 222-235. https://doi.org/10.1016/j.gloplacha.2008.09.007

Lokshin, M. and Sajaia, Z. (2004): Maximum likelihood estimation of endogenous switching regression models. The Stata Journal **4** (3), 282-289.

Maddala, G.S. (1983): Limited-dependent and qualitative variables in econometrics. Cambridge: Cambridge University Press. https://doi.org/10.1017/CBO9780511810176

Mincer, J. (1974): Schooling, Experience and Earnings. New York: NBER and Columbia University Press.

Narayanamoorthy, A. (2001): Irrigation and Rural Poverty Nexus: State-wise Analysis. Indian Journal of Agricultural Economics **50**, 40-56.

Polson, R.A. and Spencer, D.S.C. (1991): The Technology adoption process in subsistence agriculture: the case of cassava in South-western Nigeria. Agricultural Systems **36**, 65-68. https://doi.org/10.1016/0308-521X(91)90108-M

Putler, D.S. and Zilberman, D. (1988): Computer Use in Agriculture: Evidence from Tulare County, California. American Journal of Agricultural Economics **70**, 790-802. https://doi.org/10.2307/1241920

Rahm, M.R. and Huffman, W.E. (1984): The Adoption of Reduced Tillage: The Role of Human Capital and Other Variables. American. Journal of Agricultural Economics **66**, 405-413. https://doi.org/10.2307/1240918

Shah, T. and Singh, O.P. (2004): Irrigation Development and Rural Poverty in Gujarat, India: A Disaggregate Analysis. Water International **29** (2), 167-177. https://doi.org/10.1080/02508060408691766

WB (2013): World Development Indicators. Washington DC: World Bank.

Zepeda, L. (1990): Predicting Bovine Somatotropine Use by California Dairy Farmers. Western Journal of Agricultural Economics **15** (1), 55-62.