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Irrigation Impact on Crop Productivity in Tigray, Ethiopia

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ABSTRACT

This article evaluates the impact of employing irrigation on crop productivity using a dataset of over 500 farm households in Tigray Region, Ethiopia. Endogenous switching regression treatment effects approach is adopted in the study to reduce selection bias stemming from both observed and unobserved characteristics. It is found that irrigation increases crop productivity. This study supports the need for vital investments in irrigation schemes development, and efforts to improve access to modern irrigation. Over and above, development policies for agricultural transformation in the region would need to extensively encourage farmers to employ irrigation in all crop-producing areas of the region suitable for irrigation, and it should be accompanied by increasing availability of affordable irrigation schemes for the smallholder farmers to enhance their livelihood.

Key words: Endogenous switching regression, Treatment effects, Irrigation, Crop productivity, Tigray, Ethiopia

Introduction

Though Ethiopian agriculture is in protracted and deep-rooted challenges, the sector has still been the major contributor and determinant of the Ethiopian economy. It still dominantly influences the growth of other sectors. They are primarily dependent on it as a source of inputs, capital investments, and market. Many dependable sources put that it has a 34.1% (27.5 billion USD) share of the GDP, contributes over 79% to employment opportunities, and commandingly controls over 79% of foreign exchange earnings (MOA, 2020). The agriculture sector is chiefly characterized by crop production which amounts to 60% of the total outputs of the sector. The rest is livestock production and agricultural value-added outputs with 27% and 13% respectively. The sector is largely dominated by small-scale farmers who have been practicing rain-fed agriculture with traditional farming technologies for centuries (Berhanu, 2014).

In Ethiopian agriculture, the production of cereals has a lion's share in terms of both cultivated areas, which covers 81.27% of all grain crops, and volume of production. Amongst all major cereals produced, teff takes up the largest proportion and is followed by maize, sorghum, barley, wheat, millet, and rice. Similarly, as compared to all other crops produced in the sector, the annual production of cereals occupies around 87.42%. The five kinds of cereal chiefly teff, maize, wheat, sorghum, and barley are thought to be the hub of Ethiopia's agriculture and the sources of food. In sum, the production of cereal plays a pivotal role in Ethiopian agriculture in the effort to maintain sustainability in the sector (CSA, 2017). In areas where rainfall is inadequate to produce cereal crops as required, using irrigation as an agricultural technique would result in high cereal production and productivity. This will reduce reliance on rain-fed agriculture and thereby maintain stability in agricultural production and eventually will improve food security. So, to boost cereal crop yield and productivity the development and application of irrigation technology are so critical (FAO, 2018). Generally, the mean productivity of cereals namely teff, maize, rice, wheat, sorghum, and barley recorded a steady and progressive increase from 2004 to 2017. This was observed that the overall productivity of cereals increased from 1.2 t/ha in 2001 to 2.5 t/ha in 2017. The highest overall percentage increase of productivity was recorded in teff which was 112% and the lowest was that of rice with 100% in the same period. This would pave the way for seizing cereal imports from abroad and being self-sufficient domestically (IJRSAS, 2018). Production of cereals has been increasing steadily between 2016/17-2019/20. This indicates that an increase in yields and productivity has resulted from improved practices, the introduction of irrigation, and increased support to cereal crop farmers (USDA, 2020).

In Tigray Regional State the agricultural practices used for many centuries have been ox-plow cultivations which are principally characterized by the production of cereals. The technology is still persistent these days with no modification. In the region, the agriculture sector has entirely been dependent on erratic rainwater to produce crops. The rain-fed agrarian systems and coupled with fast population growth have created dire situations in the sector (World Bank, 2018). There is in general insufficient crop production in the region (Bihon, 2015). Surveyed data on the effect of utilization of irrigation in the production and productivity of cereals in the region revealed that farmers who used irrigation technologies benefited and enjoyed much higher yields and productivity of cereals than farmers who depended on rain-fed agriculture (FAO, 2018). Tigray accounts for 4% of the total chickpea production in Ethiopia with 1.3 ton/ha productivity following Amhara and Oromia Regions. Besides, it covers 7% of the total lentil production in Ethiopia with 1.21 ton/ha productivity level (Setotaw et al, 2014). The region has the potential to expand common bean production which is grown in three zones with more than five thousand tons of production (CSA 2016). In Tigray, there is only about nineteen thousand hectare crop lands that are actually irrigated and this accounted for 3.4% of the total crop land areas. About 72% of the total irrigated cropland areas in the region were under cereals while about 10%, 4%, 9% and 3% are under pulses, vegetables, fruits and stimulant crops (Adugna, 2009).

Analytical framework for assessment of irrigation impact on productivity

Establishing a suitable counterfactual against which the impact can be measured is an empirical challenge in impact assessment using observational data because of self-selection problems. Exposure to a technology should be randomly assigned to accurately measure the impact of technology adoption on productivity of farm households, so that the effect of observable and unobservable characteristics between the treatment and comparison groups is the same, and the effect is attributable entirely to the treatment. However, adoption decisions are likely to be influenced both by unobservable (e.g., managerial skills, motivation, and land quality) and observable heterogeneity that may be correlated to the outcome of interest when the treatment groups are not randomly assigned. Propensity score matching (PSM), generalized propensity score (GPS) matching in a continuous treatment framework, and instrumental variable (IV) approaches are some of the econometric approaches to deal with selection bias in cross-sectional data. PSM only controls for observed heterogeneity while IV can also control for unobserved heterogeneity. The traditional IV treatment effect models with one selection and outcome equation assumes that the impact can be represented as a simple parallel shift with respect to the outcome variable. The endogenous switching regression (ESR) framework relaxes this assumption by estimating two separate equations (one for irrigators and one for non-irrigators) along with the selection equation (e.g. Kassie et al., 2008; Di Falco et al., 2011; Kabunga et al., 2012). In this study, a binary ESR treatment effects approach is adopted to reduce the selection bias by controlling for both observed and unobserved heterogeneity.

Selection bias is one of the major econometric problems in evaluating project impacts (Maddala, 1983). Both observed and unobserved characteristics may lead to selection bias. According to (Alene & Manyong, 2007) self-selection into an intervention would be the source of endogeneity, and failure to account this bias would obscure the true impact of the intervention. Thus, the study employs endogenous switching regression model (ESR) to minimize the problems of self-selection bias and unobserved characteristics. Both endogeneity and sample selection bias are accounted for by ESR designs by estimating a simultaneous equations model using full information maximum likelihood method (Lokshin & Sajaia, 2004). Following (Lokshin & Sajaia, 2004), there are two stages, first the decision to use irrigation (selection equation) is modeled by standard limited dependent variable models, and second the outcome variable is then estimated separately for each group (as irrigation users and non-users), conditional on having the selection equation. Therefore, the selection equation is a dichotomous choice, where a smallholder farmer decides to use irrigation when there is a positive perceived difference between having the scheme and not having the scheme. Consider a farm household i that faces a decision on whether or not to use irrigation. Let U_0 represents the benefits to the farmer from the adoption of rain-fed agriculture, and let U_k represents the benefit stream from the participation in irrigation intervention. The farmer will adopt irrigation if $I_i^* = U_k - U_0 > 0$. The net benefit I_i^* that the farmer derives from the participation in irrigation scheme is a latent variable determined by observed characteristics (z_i) and the error term (ε_i):

$$I_i^* = z_i\alpha + \varepsilon_i \; With \; I_i = \begin{cases} 1 \; if \; I_i^* > 0 \\ 0 \; otherwise \end{cases} \quad (1)$$

where I_i is a binary indicator variable that equals 1 if a farmer participates in the irrigation scheme and zero otherwise and α is a vector of parameters to be estimated. The outcome functions, conditional on participation, can be written as an endogenous switching regime model:

Regime 1 : $y_{1i} = x_{1i}\beta_1 + \eta_{1i,}$ if I = 1 (2a)

Regime 2 : $y_{2i} = x_{2i}\beta_2 + \eta_{2i,}$ if I = 0 (2b)

where y_1 and y_2 are outcome variables, representing lnproductivity (hereafter productivity), for irrigators and non-irrigators, respectively; x represents a vector of covariates, and β is a vector of parameters to be estimated.

For the ESR model to be identified, it is important for the z variables in the adoption model to contain a selection instrument in addition to those automatically generated by the non-linearity of the selection model of adoption. Membership in irrigation Association is the instrumental variable used for the identification of the impact of irrigation on crop productivity outcome variable. In developing countries, social networks, such as irrigation, peasant and cooperative association, friends are the main source of information and confidence in the process of technology or new practice adoption. Hence the existence of social participation (farmer-to-farmer contact) is expected to influence use of irrigation scheme, but not the productivity of households. Thus it is considered that the variable is likely to be correlated with the adoption of irrigation but are unlikely to influence the outcome variable directly or correlated with the unobserved errors of Eqs. (2a) and (2b).

The estimation of $\beta_1$and β_2 using ordinary least squares (OLS) might lead to biased estimates, because the expected values of the error terms ($\eta_{1,}$and $\eta_{2,}$), conditional on the selection criterion, are non-zero. The error terms in Eqs. (1) and (2) are assumed to have a trivariate normal distribution with mean zero and covariance matrix specified as:

$$cov(\varepsilon, \eta_{1,}\eta_{2,}) = \begin{bmatrix} \sigma_\varepsilon^2 & \sigma_{\varepsilon 1} & \sigma_{\varepsilon 2} \\ \sigma_{1\varepsilon} & \sigma_1^2 & . \\ \sigma_{2\varepsilon} & . & \sigma_2^2 \end{bmatrix}, \quad (3)$$

Where σ_ε^2 = var(ε), σ_1^2 = var(η_1), σ_2^2 = var(η_2), $\sigma_{\varepsilon 1}$= cov(ε, η_1), and $\sigma_{\varepsilon 2}$ = cov(ε,η).

The variance of σ_ε^2 can be assumed to be equal to 1 since the β coefficients in the selection model are estimable up to a scale factor. The covariance between $\eta_1$and η_2 is not defined since y_1 and y_2 are not observed simultaneously (Maddalla, 1983). The expected values of $\eta_1$and η_2 conditional on the sample selection is non-zero because the error term in the selection Eq. (1) is correlated with the error terms of the outcome functions ($\eta_1$and η_2):

$$E(\eta_{i1}|I_i = 1) = \sigma_{1\varepsilon}\frac{\phi(z_i\alpha)}{\Phi(z_i\alpha)}$$

$$= \sigma_{1\varepsilon}\,\lambda_{i1} \text{ and}$$

$$E(\eta_{i2}|I_i = 0) = -\sigma_{2\varepsilon}\frac{\phi(z_i\alpha)}{1-\Phi(z_i\alpha)}$$

$$= \sigma_{2\varepsilon}\,\lambda_{i2},$$

where $\phi(.)$ is the standard normal probability density function, $\Phi(.)$ is the standard normal cumulative density function, $\lambda_{i1} = \frac{\phi(z_i\alpha)}{\Phi(z_i\alpha)}$ and $\lambda_{i2} = \frac{\phi(z_i\alpha)}{1-\Phi(z_i\alpha)}$. Where λ_{i1} and λ_{i2} are the Inverse Mills Ratios (IMR) computed from the selection equation and will be included in 2a and 2b to correct for selection bias in a two-step estimation procedure, i.e., endogenous switching regression. The standard errors in (2a) and (2b) are bootstrapped to account for the heteroskedasticity arising from the generated regressors (λ).

The above framework can be used to estimate the average treatment effect on the treated (ATT) and untreated (ATU) by comparing the expected values of the outcomes of irrigators and non-irrigators in actual and counterfactual scenarios. Following Carter and Milon (2005), Di Falco et al. (2011) and the wage decomposition literature, the investigator computes the ATT and ATU in the actual and counterfactual scenarios. The estimates from ESR allow for the computing of the expected values in the real and hypothetical scenarios presented in Table 1 and defined below:

Irrigators with participation (observed in the sample):

$$E(y_{i1}|I = 1, x) = x_{i1}\beta_1 + \sigma_{1\varepsilon}\lambda_{i1} \tag{4a}$$

Non-irrigators without participation (observed in the sample):

$$E(y_{i2}|I = 0, x) = x_{i2}\beta_2 + \sigma_{2\varepsilon}\lambda_{i2} \tag{4b}$$

Non-irrigators had they decided to participate in the scheme (counterfactual):

$$E(y_{i1}|I = 0, x) = x_{i2}\beta_1 + \sigma_{1\varepsilon}\lambda_{i2} \tag{4c}$$

Irrigators had they decided not to participate in the scheme (counterfactual):

$$E(y_{i2}|I = 1, x) = x_{i1}\beta_2 + \sigma_{2\varepsilon}\lambda_{i1} \tag{4d}$$

Eqs. (4a) and (4b) represent the actual expectations observed from the sample, while Eqs. (4c) and (4d) are the counterfactual expected outcomes. Using these conditional expectations the following mean productivity outcome difference can be computed. The expected change in irrigator's productivity, the effect of treatment on the treated (ATT) is computed as the difference between (4a) and (4d):

ATT = E(y_{i1}|I = 1, x) - E(y_{i2}|I = 1, x)

$$= x_{i1}(\beta_1 - \beta_2) + \lambda_{1i}(\sigma_{1\varepsilon} - \sigma_{2\varepsilon}) \quad (5)$$

Similarly, the expected change in non- irrigator's productivity, the effect of the treatment on the untreated (ATU) is given as the difference between (4c) and (4b):

ATU = E(y_{i1}|I = 0, x) - E(y_{i2}|I = 0, x)

$$= x_{i2}(\beta_1 - \beta_2) + \lambda_{2i}(\sigma_{1\varepsilon} - \sigma_{2\varepsilon}) \quad (6)$$

The first term on the right hand side of Eq. (5) represents the expected change in irrigator's mean outcome, if irrigators' characteristics had the same return as non- irrigators, or if irrigators had similar characteristics as non- irrigators. The second term λ is the selection term that captures all potential effects of difference in unobserved variables. Similarly, for the effect of treatment on the untreated, the first term in (6) can be interpreted as the expected change in the non- irrigators mean outcome if non- irrigators' characteristics had the same return as irrigators or if non- irrigators had similar characteristics as irrigators. The second term adjusts the ATU for the effect of unobservable factors.

Table 1. Expected conditional and average treatment effects in the ESR framework

Sample	Decision stage		Treatment effect
	To irrigate	Not to irrigate	
Irrigators	(4a) E(y_{i1}|I = 1, x)	(4d) E(y_{i2}|I = 1, x)	ATT
Non- irrigators	(4c) E(y_{i1}|I = 0; x)	(4b) E(y_{i2}|I = 0, x)	ATU

DATA

The data utilized for this study is acquired from farm household survey undertaken during 2015/16 by Ethiopian Institute of Agricultural Research (EIAR) in collaboration with the International Fund for Agricultural Development (IFAD). A total of 518 farm households in 6 "woredas" (districts) and 6 'Kebeles' (villages/local councils) from Tigray Regional State were interviewed. The main types of crop grown by the households in our sample were teff (Eragrostis tef), wheat, maize, barley and sorghum. Some households grew pulses, vegetables or fruits. A Two-stage Random Sampling method was employed, and the primary sampling was carried out to select 'Kebeles' from project intervention areas while the secondary sampling was undertaken to select sample farm households from selected 'Kebeles'. The data was collected using a pre-tested interview schedule by trained and experienced enumerators who speak the local language and have good knowledge of the farming systems.

RESULTS AND DISCUSSIONS

Descriptive statistics

Some demographics and socio economic characteristics of the sample population of the irrigation users and non-users are presented in Table 2.

Table 2. Descriptive statistics of important variables used in the Endogenous Switching Regression

Variables	Unit	Irrigators Mean(se)	Non-irrigators Mean(se)	Aggregate Mean(se)	t-stat.
Outcome variable					
lnproductivity	#	7.58(0.16)	6.88(0 .05)	6.97(0 .05)	-5.43***
Variables that affect probability of adoption					
HHAGE	#	44.62(1.45)	45.68(0.63)	45.53(0.58)	0.63
HHEDU	#	3.94(0.41)	2.47(0.14)	2.68(0.14)	-3.79***
LANDSIZE	ha	1.05(0 .08)	1.32(0.05)	1.28(0 .04)	2.21**
ImprovedSeed	1=Yes	0.49(0.06)	0.19(0.02)	0.23(0.02)	-5.42***
Chemfert	#	29.04(6.59)	19.38(4.06)	20.74(3.62)	-0.93
Pesticide	#	236.42(74.00)	15.44(5.00)	46.41(11.71)	-6.87***
Laborcost	#	422.62(149.29)	57.53(17.55)	108.69(26.34)	-4.93***
Prodasset	#	1.71(0 .12)	1.60(0.04)	1.61(0.04)	-1.00
DistanceMarket	#	116.83(3.75)	146.00(9.16)	120.89(3.50)	2.88***

*, ** and *** represent significance at 0.1, 0.05 and 0.01 levels respectively.
Source: own computation (2021)

Households using irrigation have higher positive and significant average crop yields than households relying on rain-fed agriculture. In addition, irrigating households are better educated than non-irrigators. Irrigation users have higher farm input expenditures on improved seeds, pesticides and labour than households using rain-fed agriculture, but there was no significant difference in terms of fertilizer investments between irrigators and non-irrigators. However, non-irrigators possess larger landholding size than those farm households that participate in irrigation as adopters are technology intensive to compensate for the lower total crop production by raising productivity level.

Endogenous switching regression estimation results

The dependent variable is binary participation in irrigation. The various test of goodness-of-fit indicate that the selected covariates provide good estimate of the conditional density of irrigation. For example, the Wald chi2 test statistic (34.01) indicates that explanatory variables are jointly statistically significant ($P < 0.01$). Besides, the likelihood ratio test of independence of equations (for productivity conditional on the selection equation test) rejects the hypothesis that the equations are jointly independent.

Table 3. Average treatment effects with endogenous switching regression model

Outcome variable	**Mean**		**Average Treatment effects**
	Irrigation user	Non-user	
lnproductivity	7.580256	6.535855	ATT= 1.044401***
	7.735495	6.948392	ATU= 0.7871025***
			T H = 0.2572987***

*, ** and *** represent significance at 0.1, 0.05 and 0.01 levels respectively.
Source: own computation (2021)

As we see from the last column of Table 3, both irrigators and non-irrigators would benefit from employing irrigation. This shows that employing irrigation increases productivity. Households who actually irrigated would have more than 50% less productivity had they not employed irrigation. This is the average treatment effect on the treated (ATT) which is statistically significant. Similarly, households that did not use irrigation, would have about above 100% more productivity if they had participated in the irrigation scheme, implying that current non-irrigators would have realized higher levels of productivity from switching to irrigation use under the given conditions. This is the average treatment effects on the untreated (ATU) which is also statistically significant. Treatment heterogeneity-TH (impact), that is, the difference between ATT and ATU is 29%. This shows that the irrigators enjoy higher productivity owing to their participation in the intervention. The intervention in general has brought a significant positive impact of 29% as seen by comparing the average treatment effect on the treated (ATT) with the average treatment effect on the untreated (ATU).

Conclusion and Recommendation

The effects of irrigation on crop productivity among smallholder farmers in Tigray are analyzed in this study. And a rich farm household survey is used to estimate these effects by employing an endogenous switching regression treatment effects approach utilized to mitigate biases stemming from both observed and unobserved heterogeneity. Results indicate that irrigation has generated a significant positive impact on crop productivity. Farm households that did adopt the technology would benefit the most from participating in the irrigation scheme. At the household level, the ATT, which is the actual effect on the crop productivity outcome variable that irrigators experience through participating in the irrigation scheme, is significant and positive and so are the Average Treatment Effect on the Untreated and the Treatment Heterogeneity. Therefore, development policies for agricultural transformation in Tigray would need to extensively encourage farmers to employ irrigation in all crop-producing areas of the region, and it should be accompanied by increasing availability of affordable irrigation schemes for the smallholder farmers to enhance their livelihood.

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