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Full Length Research Paper

Irrigation access and per capita consumption expenditure in farm households: Evidence from Ghana

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Investment in agricultural water management has been one key poverty reduction strategy in developing countries. In Ghana, irrigation development for livelihood support, which dates back to the 1960s manifested in the development of formal irrigation infrastructure, starting with the rural savannah and coastal regions. This study applied a propensity score matching (PSM) approach and regression analysis (ordinary least squares and switching regression) to ascertain that, pro-poor irrigation investment in the rural savannah region of Ghana is justified due to significant irrigation contribution to consumption expenditure per capita in farm households. The results also show differences in the impacts of irrigation access on household consumption expenditure per capita due to differences in the methodologies employed. The gain in household consumption expenditure per (GH¢) using the different methodologies are as follows: Propensity Score Matching approach (GH¢ 24.90, GH¢28.30), ordinary least squares regression (GH¢ 5.40), and switching regression (GH¢23.70). Thus, the range of estimates of irrigation's impact on household consumption expenditure is positive (GH¢ 5.4 to GH¢ 28.3). The differences in the magnitude of these estimates are ascribed to the underlying assumptions and robustness of each of these methodologies employed in the study.

Key words: Irrigation, consumption expenditure, propensity score matching, ordinary least squares regression, switching regression, Ghana.

INTRODUCTION

A review of past successes in poverty reduction suggests investment in agriculture (*viz.* irrigation) as a key strategy (Lipton et al., 2003). In developing countries, one prominent and hopeful strategy for mitigating poverty has been the promotion of agricultural activities through investment in agricultural water management, a key pre-condition for agricultural growth (van Koppen et al., 2005). Irrigation constitutes by far the largest investment in the agricultural sector in developing countries (Bhattarai and Narayanamoorthy, 2003).

In Ghana, the agricultural sector continues to be driven by rainfed practices resulting in low productivity and output (ISSER, 2006). The sector is still dominated by a high mass of rural-based small-scale food producers. Irrigation practice has been relatively minimal. Available data show total irrigated area to be just about 0.26% of total cultivated area in 2006 (MoFA-SRID, 2007). The realisation of the role of irrigation in Ghana's agricultural development dates back to the 1960s. This was manifested in the Northern and Coastal zones of Ghana where a significant investment in irrigation infrastructure was made against the backdrop of drought conditions in these areas (GIDA, 2002).

Extensive implementation of liberalisation and adjustment policies in the 1980s did little to induce sustained growth in agriculture and manufacturing in Ghana. Both growth and incomes remained stagnant resulting in deepening poverty (GoG, 2005). The incidence of extreme poverty (60.1%) has been very pronounced in the rural savannah areas of the three Northern regions contributing the highest proportion (49.3%) of total poverty in Ghana (GSS, 2007). The impact of improved water control for crop production activities, unlike in Sub-Saharan Africa, has been documented quite extensively in other parts of the world such as Asia where considerable

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investments in water management for irrigation have been made. Asian research findings consistently indicate that irrigation development reduces poverty in rural areas (Mellor and Desai, 1985; Chambers et al., 1989; Hossain, 1989; Hussain and Hanjra, 2003). According to Saleth et al. (2003), the fundamental routes through which investments in agricultural water management (irrigation) affects poverty, are the production or productivity effects, and employment or income effects. However, as revealed by Comprehensive Assessment of Water Management in Agriculture (CAWMA) (2007), these effects can be direct or indirect, positive or negative. The effects include changes in food production, employment, food prices/ consumption, empowerment, risk and vulnerability, education and capacity. Other studies also establish a link between access to irrigation and improvement in household welfare primarily through improved cultivation intensity and yields (Datt and Ravallion, 1998; Hussain and Giordano, 2004; Adeoti et al., 2007); increased incomes and consumption (Rozelle, 1996; Diao et al., 2005; Huang et al., 2006; Hussain, 2007); and created employment through the engagement of communities in dam construction and improved demand for hired labour (Chambers, 1988; Barker et al., 2000).

To the best of our knowledge, relevant studies on irrigation-poverty linkages have been less explicit on the magnitude of irrigation impacts on household poverty conditional on membership in irrigation project. This paper presents the results of a study conducted on the effects of access to irrigation on farm household consumption expenditure per capita in the *Tolon-Kumbungu* district of Ghana.

RESEARCH METHODOLOGY

The study was carried out on two formal irrigation schemes (*Bontanga* and *Golinga*) in the *Tolon-Kumbungu* district in Northern Ghana. The *Tolon-Kumbungu* District was carved out of the West Dagomba District in 1998. The district's economy is typically agrarian where potential for year-round irrigated farming is high along the banks of the White Volta and on the two biggest dams- *Bontanga* and *Golinga*. These districts host a sizeable number of the citizenry engaged in the cultivation of vegetables and cereals (www.ghanadistricts.com). Due to the promotion of dry season farming, markets such as the *Tamale* Municipality are supplied year round with vegetables. Rains begin in May and end in the latter part of October. July to September is the peak period of rain giving rise to rampant flooding. The average annual rainfall is 1000 mm.

The *Bontanga* irrigation scheme was constructed beginning 1980, but crop production commenced in 1987. The project caters for seventeen (17) surrounding villages. The gross area under the scheme is 570 ha. The dam water flows through surface canals by gravity. Cropping is carried out in two main seasons. In the rainy season (May to October), rice, corn and cowpea are cultivated. Dry season (October to April) crops include rice, onion, okro, tomato, pepper and cowpea. Fresh vegetables are sold within the *Tamale* Municipality and nearby marketing centers. The bulk of the onion produced is sold in the southern markets of Kumasi and Accra. The average farm size on the scheme is about 0.6 ha (1.5 acres) (Preliminary survey in October, 2007).

The *Golinga* irrigation scheme on the other hand was put into production in 1973. The scheme serves five surrounding communities, being relatively smaller (33 ha of irrigable land). Water in the dam, like that of *Bontanga*, flows by gravity through surface canals. The main crop cultivated is rice but sometimes vegetables are also cultivated. Cultivation on the scheme is done mostly in the dry season whiles rainy season activities are shifted onto upland rainfed areas. There is ready market for produce bought mostly at the farm gate. Farm sizes range from 0.2 to 0.4 ha (Preliminary survey in October, 2007).

From the point of view of management, membership in both *Bontanga* and *Golinga* irrigation projects was purposely based on ethical and sustainability considerations. In the assignment process, victims of the negative effect of the dam construction were first considered. Farmers in closer communities to the scheme were next considered for scheme lands before all others. However, owing to limited scheme land and the need to engender a sense of community ownership (in all surrounding communities) there are situations where some farmers in farther communities rather own scheme lands. But generally, being a victim and closeness to scheme are two variables strongly determining membership.

The study utilizes both qualitative and quantitative data that are collected from a cross-section of irrigating and rainfed farmers in the study areas. A predominantly structured questionnaire was used in the study. The questionnaire covers data on irrigation adoption decisions of households a year before they entered into the scheme. The same set of adoption decision data are gathered from non-irrigating farmers. Data on household production activities, incomes, consumption expenditure, asset base, social participation and participatory decision-making are also solicited by close-ended questions. Apart from data on irrigation adoption decision, all other data are in current (past production year) terms.

A stratified random sampling technique was used to select the irrigating farmers. The reason for stratification is that differences exist in the distribution of water in the head-tail ends of the schemes. Hence to ensure a fair representation a list of the irrigating farmers was obtained from scheme management, and farmers stratified according to their location on the scheme. From these strata, simple random selection was done to obtain seventy (70) farmers for each of the two schemes. Further, eighty (80) and seventy (70) rainfed farmers residing around Golinga and Bontanga schemes, respectively, were purposively sampled once the interviewer was within the locality. For this group, a sampling frame was non-existent. Propensity score matching method is data demanding in terms of sample size. This is because, an appropriate rainfed group matches for the irrigating group must be identified based on predicted probabilities. A large sample increases the possibility of finding a large matching group for the irrigating farmers. Large samples also ensure good statistical reliability for estimates.

Given these considerations, 150 rainfed farmers were considered adequate for comparison with a sample of 140 irrigating farmers. In all 290 farmers were interviewed. STATA, Eviews and SPSS softwares were used for the analysis.

Propensity score matching approach (PSM)

In analysing the impact of irrigation on outcome means, the method of matching based on propensity scores is applied. Analysing the impact or gain of project interventions requires the establishment of the requisite counterfactual that represents what would have happened had the project not taken place or what otherwise would have been true (Baker, 2000). The establishment of this counter-factual often poses a daunting task in *ex post* project analysis where before intervention situation remains missing. Under such circumstances appropriate estimation of the counterfactual is established by way of a comparative group that does not participate in the intervention. In projects, where participants were selected purposively rather than at random, the problem of 'selection bias' is often encountered in evaluation of impacts. Therefore analysis of the impact based on a 'with and without' approach yields inaccurate results (Friedlander and Robins, 1995), and any attempt to net out actual project impact must factor in the underlying selection process (Zaman, 2001).

Assignment to participate in irrigation in the study sites was purposively done. Owing to this mode of assignment, the PSM framework is adopted for estimating the impact of irrigation access on household per capita consumption[1]. Impact through this outcome variable is obtained by matching an ideal comparative group (non-irrigating farmers) to the treatment group (irrigating farmers) on the basis of propensity scores (P-scores) of X. X is the set of observable characteristics that determine irrigation participation. By so doing the selectivity bias is (largely) eliminated.

To develop the PSM framework, let Y_i be the outcome variable of household *i*, such that Y_{1i} and Y_{0i} denote household outcomes with and without access to irrigation, respectively. A dummy variable I_i denotes irrigation access by household *i*, where $I_i = 1$ if the household has access to irrigation and $I_i = 0$, otherwise. The outcome observed for household *i*, Y_i is defined by the switching regression (Quandt, 1972).

$$Y_i = I_i Y_{1i} + (1 - I_i) Y_{0i} \quad (1)$$

The impact of irrigation on household *i*'s consumption expenditure per capita is given by;

$$\Delta_i Y_i = Y_{1i} - Y_{0i} \quad (2)$$

Where $\Delta_i Y_i$ denotes the change in the outcome variable of household *i*, resulting from access to irrigation.

A household cannot be both ways, therefore, at any time, either Y_{1i} (irrigating household) or Y_{0i} (non-irrigating household) is observed for that household. This gives rise to the selectivity bias problem (Heckman et al., 1997). The framework assumes heterogeneity in impacts of outcomes (household per capita consumption) and a stable-unit-treatment value (SUTV). The heterogeneity assumption is important because, practically all households with access to irrigation cannot benefit equally as a result of differing characteristics. The SUTV assumption implies that, the impact is confined within households such that possible interaction effects are ruled out (Cobb-Clark and Crossley, 2003).

The most commonly used evaluation parameters are averages (Heckman et al., 1997). Two means are common in the impact analysis framework, the average treatment effect, (ATE) and the average treatment effect on the treated (ATT). In the case of irrigation, ATE estimates the effect of irrigation on the outcomes of the whole population without regards to irrigation but the ATT estimates irrigation effects conditional on access to irrigation water. It is the latter which this study seeks to estimate and it is represented as;

$$\text{ATT}=[E(\Delta_i | I_i = 1)] = E[Y_{1i} - Y_{0i} | I_i = 1] = E[Y_{1i} | I_i = 1] - E[Y_{0i} | I_i = 1] \quad (3)$$

[1] In this study, household consumption expenditure per capita has been used as a proxy for welfare. This paper is a follow up of Owusu et al., (2011).

From (3), $E[Y_{0i} | I_i = 1]$ is the missing data representing the outcomes of irrigation participants in the absence of irrigation. One way to estimate this missing data is to use outcomes of a non-irrigating group. By using the outcomes of a non-irrigating group, (3) can be rewritten as

$$[E(\Delta_i | I_i = 1)] = E[Y_{1i} | I_i = 1] - E[Y_{0i} | I_i = 0] \quad (4)$$

Without controlling for the unobservable heterogeneity, (4) can be shown to consist of a bias in addition to the impact estimate. Subtracting and adding $E[Y_{0i} | I_i = 1]$ to the right hand side of (4) gives

$$E[Y_{1i} | I_i = 1] - E[Y_{0i} | I_i = 0] - E[Y_{0i} | I_i = 1] + E[Y_{0i} | I_i = 1] \quad (5)$$

Rearranging (5) gives,

$$= E[Y_{1i} - Y_{0i} | I_i = 1] + \underbrace{E[Y_{0i} | I_i = 1] - E[Y_{0i} | I_i = 0]}_{\text{Bias}} = E[\Delta_i | I_i = 1] + \{E[Y_{0i} | I_i = 1] - E[Y_{0i} | I_i = 0]\} \quad (6)$$

Thus, a bias of the magnitude shown in (6) results when non-irrigating farmers are selected for comparison with irrigating farmers, without controlling for the non-random irrigation assignment (Cobb-Clark and Crossley, 2003; Ravallion, 2005).

The PSM method takes care of the bias, so that estimated irrigation impact is largely consistent. The method identifies and matches households within the non-irrigating group that are similar in observable characteristics (X_i), to those of the irrigating group. This is done by deriving propensity scores[2] from a binary logit estimation of irrigation participation model (Dehejia and Wahba, 2002). A binary logit model can be represented as,

$$\Pr(I_i = 1 | X) = \frac{1}{1+e^{-\beta X}} = \Pr(X), \quad (7)$$

Where X is a vector of explanatory variables including household characteristics and criteria for placement, which are deemed to influence access to irrigation; Pr (X) is the propensity score. Based on the propensity scores of irrigating and non-irrigating farmers, the nearest neighbour matching is used to select the 'best' non-irrigating group for the irrigating group.

Rosenbaum and Rubin (1985) opine that, since exact matching is rarely possible, an issue of closeness must be considered. Matching therefore uses the expected outcomes of the non-irrigating group (without irrigation), conditional on the propensity scores to estimate the expected counterfactual of the irrigating farmers (Cobb-Clark and Crossley, 2003). Thus the relation, holds, only when the assumption of closeness of propensity scores is valid (common support assumption).

$$\{E[Y_{0i}], I_i = 1, X_i = x\} = \{E[Y_{0i}], I_i = 0, X_i \approx x\} \quad (8)$$

[2] The propensity scores, P(X) = Pr ($I_i = 1 | X_i = x$), give the probability of participation in the irrigation program conditional on a vector of household characteristics, X_i .

The 'conditional independence' or 'exogeneity' assumption must hold for this relation to be true. Rosenbaum and Rubin (1985) showed that once appropriate common support is established the conditional independence assumption becomes valid. They proved that, if outcomes without irrigation (Y_{0i}) are independent of participation in irrigation (I_i) given $X_i = x$, then participants are also independent of participation (I_i) given their propensity scores [P(X)].

In PSM irrigation participation characteristics are used to estimate a single value (P-score) which serve as the basis of comparison rather than the characteristics themselves. The latter could be very laborious; hence PSM solves the 'curse of dimensionality'. Once common support is established for the irrigating group, the heterogeneous impact (ATT) of irrigation on household consumption expenditure per capita can then be estimated using Equation (9).

$$ATT = [E(\Delta_i | I_i = 1)] = \frac{1}{I_i}\Sigma(Y_{1i} - E[Y_{0i}])I_i = \frac{1}{I_i}\Sigma\Delta_i I_i \qquad (9)$$

Irrigation impacts on incomes by increasing farm revenues. The impact of irrigation on farm incomes would likely increase farm household expenditure, all things being equal. Huang et al. (2006) found that, irrigating households[3] realised 79% higher revenues than non-irrigating[4] households. The difference was chiefly ascribable to the possibly higher yields, increased intensity and switch to high-value crops. They used the fixed effect framework to also verify the magnitude of irrigation impacts on income. Their multivariate analysis showed that increasing irrigated area[5] by one hectare increased both cropping and total incomes by 3028 Yuan and 2628 Yuan, respectively. They inferred that since crop income accounts for a much higher percentage of total household income of poorer households, a positive impact on crop income coupled with the structural characteristics of household income suggest a poverty reduction role of irrigation. Diao et al. (2005) also reported higher incomes by as much as 50% in irrigated settings compared to non-irrigated areas.

In their review of empirical support of irrigation in poverty reduction, Hussain and Hanjra (2003) concede that although empirical studies do not use common income categories and yardsticks to allow meaningful inter-comparisons, whatever the metric used, it is not uncommon to find 50% higher incomes in irrigated settings than in rainfed areas. Studies in Vietnam, Thailand, Philippines and India show that the depth of poverty ranged from 5.4 to 11.0% in irrigated settings and from 13.3 to 33.4% in rainfed settings (Ut et al., 2000; Isvilanonda et al., 2000; Hossain et al., 2000; Thakur et al., 2000; Janaiah et al., 2000). Similarly, income inequalities are slightly higher in rainfed settings (0.34 to 0.61) than in irrigated settings (0.30 to 0.53). A study in Sri Lanka's WLB System compares irrigating farmers to non-irrigating farmers and results show that household incomes were higher in irrigated areas than in non-irrigated areas (Hussain and Hanjra, 2003). Average monthly household expenditure was 24% higher in irrigated areas than in non-irrigated areas. Thus, access to irrigation infrastructure enables households to smooth their consumption. They also report of a similar study in Pakistan where as a result of irrigation, crop incomes improved by 12 to 22%. Bhattarai et al. (2002) also found higher net farm incomes in irrigated settings (77%) than rainfed settings from a study in Bihar, India.

[3] Households that have access to irrigation for crop production activities.

[4] Households that have no access to irrigation for crop production, and typically do rainfed production.

[5] The authors account for irrigation in the model in terms of the extent or size of plot irrigated by a farmer, possibly because of a high degree of variation in the area of plots irrigated.

The ordinary least squares regression model of household consumption expenditure per capita (welfare)

A simple linear model is used to analyse the relationship between irrigation as an intervention variable and household welfare (per capita consumption). Following Chong et al. (2004), Andersson et al. (2006) and Johannsen (2006), the welfare model has logarithm of consumption per capita (C_i) as the dependent variable and a vector of individual, household and community variables (X_{im}) as potential determinants of household consumption expenditure per capita. The welfare model is specified in Equation (10) as follows:

$$log C_i = \alpha + \beta I_i + \sum_m^M \theta X_{im} + \varepsilon_i, \qquad (10)$$

Where, ε_i *~N(0,1)*

The ordinary least squares regression is used to estimate the parameter of interest, β. This shows the relationship between irrigation (*I*) and household welfare (consumption per capita) given other welfare determinants (X_{im}). The β estimate is consistent and unbiased once the assumptions of normal and homoskedastic residuals are not violated.

The switching regression model of household consumption expenditure per capita (welfare)

The switching regression model of household consumption expenditure per capita intuitively involves separate estimations for irrigator and non-irrigator sub-samples due to the possible systematic differences in mode of access and participation in an irrigation project. Irrigation participation thus becomes the selection criterion governing observation household consumption expenditure per capita. Depending on the assumption regarding the relationship between the residuals of the selection regime and the outcome equations, both exogenous and endogenous switching regressions can be developed (Foltz, 2004). Letting I_i represent an irrigation participation dummy where $i \in [0,1]$, an irrigation selection criterion function can be expressed as

$$I_i = \gamma' Z_i + u_i \qquad u_i \sim IIN(0,1). \qquad (11)$$

where, Z_i is a vector of household, farm and village characteristics, as well as instruments deemed to influence irrigation participation or adoption decision of household i, γ is the vector of parameters to be estimated, and u_i is the error term. Also let Y_i represent the level of household consumption expenditure. Based on the irrigation selection criterion function of Equation (11), outcome (Y_i) are observed for two different regimes (Maddala, 1983; Gebregziabher, 2008).

$$Y_{1i} = \beta_1' X_{1i} + v_{1i} \quad \text{if and only if} \quad \gamma' Z_i + u_i > 0 \; : \text{Irrigators } (I_i = 1) \qquad (12)$$

$Y_{2i} = \beta_2' X_{2i} + v_{2i}$ if and only if $\gamma' Z_i + u_i \leq 0$: Non-irrigators $(I_i = 0)$ (13)

Where, X_i is a vector of exogenously determined variables of household i, β is the coefficient vector, and v_i, the residuals.

Following Foltz (2004), we first assume that the unobserved residual effects on household consumption expenditure per capita between irrigators and non-irrigators are independent of the unobserved effects on irrigation participation condition. That is

$E[v_{1i}|I_i = 1] = E[v_{2i}|I_i = 0] = 0$, and $\text{Cov}(u_i v_i) = 0$

This implies that sample partitioning between irrigators and non-irrigators is entirely exogenous to their behaviour so that an exogenous switching structure results, as in equations (11) and (12). The unconditional expectation of these models can be expressed as Applying least squares to equations (14) and (15) gives consistent estimate of the β.

$$E[Y_{1i}|x_{1i}] = \beta_1' X_{1i} \quad (14)$$

$$E[Y_{2i}|x_{2i}] = \beta_2' X_{2i} \quad (15)$$

However, there is a high likelihood that uncontrolled factors (e.g. farmer's inherent managerial ability) in the disturbance term, u_i, influencing participation in irrigation also simultaneously influences the level of outcomes (that is, net farm income and hence household consumption expenditure per capita), so that $cov(u_i v_i) \neq 0$. Under this scenario sample separation between irrigators and non-irrigators become endogenous to their behaviour, and governed by an irrigation participation regime. Here the expected values of the error terms in the outcome equations conditioned on the sample selection is non-zero and least squares renders estimated coefficients inconsistent and inefficient (Freeman et al., 1998). Here, the error terms v_{1i}, v_{2i} and u_i are assumed to follow a trivariate normal distribution with mean vector zero and covariance matrix (Maddala, 1983; Lokshin and Sajaia, 2004).

$$\Sigma = \begin{bmatrix} \sigma_u^2 & \sigma_{1u} & \sigma_{2u} \\ \sigma_{1u} & \sigma_1^2 & \cdot \\ \sigma_{2u} & \cdot & \sigma_2^2 \end{bmatrix}$$

Where, σ_u^2 is the variance of the error term in the selection equation, σ_1^2 and σ_2^2 are the variances of the error terms in the continuous equations; σ_{1u} is the covariance of u_i and v_{1i}; and σ_{2u} is the covariance of u_i and v_{2i}. As can be deciphered, the covariance between v_{1i} and v_{2i} is not defined as Y_{1i} and Y_{2i} are never observed simultaneously. It is assumed that $\sigma_u^2 = 1$, since γ is estimable only up to a scalar factor (Maddala, 1983). The expected (conditional) outcomes of net farm income and hence household consumption expenditure per capita for the two regimes are expressed as

$$E(Y_{1i}|I = 1) = \beta_1' X_{1i} + \sigma_1 \rho_1 W_{1i} \quad (16)$$

$$E(Y_{2i}|I = 0) = \beta_2' X_{2i} - \sigma_2 \rho_2 W_{2i} \quad (17)$$

Where σ_1 and σ_2 are the standard deviations of the two outcome equations, respectively; ρ_1 is the correlation coefficient between v_{1i} and u_i; ρ_2 is the correlation coefficient between v_{2i} and u_i. W_{1i} and W_{2i} are the non-selection hazard terms[6] for the respective regimes. The model in (15) and (16) are identified by construction through nonlinearities. The models can be fitted one equation at a time by either two-stage least squares or maximum likelihood estimation. However, both estimation methods are inefficient and require potentially cumbersome adjustments to derive consistent standard errors (Lokshin and Sajaia, 2004). In order to obtain consistent standard errors, the full information maximum likelihood (FIML) method was employed to simultaneously fit the binary and continuous parts of the model. This approach relies on joint normality of the error terms in the binary and continuous equations.

Given the assumption with respect to the distribution of the disturbance terms, the logarithmic likelihood function for the system of Equations in (16) and (17) is

$$InL = \sum_i (I_i \omega_i \left[In\{F(\eta_{1i})\} + In\left\{\frac{f\left(\frac{v_{1i}}{\sigma_1}\right)}{\sigma_1}\right\}\right] + (1 - I_i)\omega_i [In\{1 - F(\eta_{2i})\} + In\left\{\frac{f\left(\frac{v_{2i}}{\sigma_2}\right)}{\sigma_2}\right\}])$$

where $F(\cdot)$ is a cumulative normal distribution function, $f(\cdot)$ is a normal density distribution function, ω_i is an optional weight for observation i, and $\eta_{ji} = \frac{(\gamma Z_i + \rho_j v_{ji}/\sigma_j)}{\sqrt{1-\rho_j^2}}$; $j = 1, 2$; where, $\rho_1 = \sigma_{1u}^2 / \sigma_u \sigma_1$ and $\rho_2 = \sigma_{2u}^2 / \sigma_u \sigma_2$.

Hypothesis

For the switching regression model, the hypothesis is as follows:

H_0: There is *no significant difference* between the means of predicted consumption expenditure per capita of irrigating and non-irrigating households, that is, $\Delta_{\widehat{Ycexp}} = 0$

H_a: The mean of predicted consumption expenditure per capita of irrigating households *is significantly higher* than that of non-irrigating households, that is $\Delta_{\widehat{Ycexp}} > 0$ Where, $\Delta_{\widehat{Ycexp}}$ is the impact of irrigation on predicted household consumption expenditure per capita. Table 1 shows the description of variables in the welfare model.

RESULTS

Socio-economic variables: Age, gender, marital status and education

Information on the socio-economic profile of respondents

[6] The non-selection hazard term otherwise known as the inverse Mills ratio is the ratio of the probability density function (pdf) to the cumulative distribution function (cdf) of a standard normal evaluated at $\gamma' Z_i$.

Table 1. Description of variables in the welfare model.

Variable	Description	Measurement
AGE	Age of household head	Continuous
GENDER	Gender of household head	Dummy: 1 for male; 0 for female
YRSC	Years of formal education of household head	Continuous
SCUL	Size of cultivated land (hectares)	Continuous
FREXT	Frequency of extension visits (number per year)	Continuous
LTINC	Logarithm of total income	Continuous
AFCRE	Ease of access to formal credit	Dummy: 1 for easy access, 0 for otherwise
AICRE	Ease of access to informal credit	Dummy: 1 for easy access, 0 for otherwise
LGLIVS	Logarithm of the value of livestock holdings	Continuous
EASM	Ease of access to market	Dummy: 1 for easy access, 0 for otherwise
LGNIINCPC	Logarithm of non-irrigation income per capita	continuous
IRRI	Access and use of irrigation water	Dummy: 1 for access/use, 0 for otherwise
LCONSPC	Logarithm of the value of consumption expenditure per capita	Continuous

Table 2. Descriptive statistics of relevant variables.

Description	Means		t
	Irrigators	Non-irrigators	
Age of household head	51	52	-0.326
Years of schooling	9	8	0.328
Dependency ratio	2.4	1.9	2.155**
Total household income per capita (GH¢)	70.7	35.8	5.387***
Size of livestock (TLUs)	3.0	4.0	-1.308*
Size of land under irrigation (ha)	0.5	-	-
Size of land under rainfed (ha)	2.9	2.8	0.425
Frequency of extension advice per year	2.4	1.8	3.797***
Ease of access to output markets: 1=easy access, 0 otherwise	-	-	-
Ease of access to informal credit: 1=easy access, 0 otherwise	-	-	-
Household land covered by dam: 1=yes, 0 otherwise	-	-	-
Shortest distance from residence to scheme (km)	3.1	3.7	2.470***
Location of settlement farm plot: 1=*Bontanga* , 0 otherwise	-	-	-
Irrigation participation: 1=irrigation use, 0 otherwise	-	-	-
Net farm income per ha (GH¢)	1020.0	563.8	3.449***
Household consumption expenditure per capita (GH¢)	230.0	207.3	1.610*

***, ** & * show significance at 1, 5 and 10% levels, respectively.

is presented in Table 2. Average age of both irrigators and non-irrigators *ex post*[7] is 51 and 52 years, respectively having increased from *ex ante*[8] values of 29 and 27 years respectively. In both periods however, statistical tests did not unearth any significant difference in age between irrigators and non-irrigators. This is attributable to the fact that both groups belong to the same population and the variable in question does not lend itself to change based on irrigation participation or otherwise. However the higher *ex post* age for both groups suggest an ageing farmer population, with the much younger energetic youth possibly switching to more lucrative ventures.

For both categories of producers, between 94 to 100% are males as against 6% of female producers. Production activity in the Tolon-Kumbungu district is thus male-dominated. The observed low proportion of female producers can be ascribed to the local or traditional norm that enshrines males as heads households and heads of households' major production activity for that matter. And for a study with the head of household as the target for interview, low female representation should be expected. For the female irrigators, some reasons for their championing household production activities on scheme

[7] This is operationalised as the study period or year.
[8] This is operationalised as the year prior to scheme inception/irrigation project participation.

lands include closer ties with land lords who were involved in land allocation, status as widows or plot inheritance from deceased husbands. With regards to marital status, majority (99%) of both irrigators and non-irrigators are married. The rest are either single or separate/divorced (Table 2). Information on the highest level of education attained by respondents show that majority (91%) of irrigators and 96% of non-irrigators have not had any formal education. The rest who have been through the formal system have had average schooling years of 7 and 8, respectively (Table 2).

Household size

The distribution of household size shows ex ante values of 8 and 7, respectively, for irrigators and non-irrigators. This increased significantly[9] to 13 for irrigators and 12 for non-irrigators in the ex post period under consideration (Table 2). However no significant difference exists between household sizes for irrigators and non-irrigators in both pre-participation and post-participation periods. This shows an increasing household size to date, and access to irrigation may have had no influence on increasing household size in the District. It is noteworthy that, larger family size can reduce household welfare if there has not been any significant improvement in productive resources or income-generating activities for the household (Grootaert et al., 1995). On the other hand, larger size of household with high proportion of economically active members is relevant for household welfare security (Glewwe et al., 2000).

Size of land holdings

Average holding size for irrigating farmers *ex ante* is about 6.72 acres (2.68 ha), as compared to 6.78 acres (2.71 ha) for non-irrigating farmers. These have increased respectively to 8.83 acres (3.53ha) and 7.1 acres (2.84 ha) in the *ex post* period (Table 2). The non-significance in mean difference of *ex ante* sizes for irrigators and non-irrigators should be expected owing to similarity in farming characteristics in the large population. However for irrigators, the significantly higher[10] size of land holdings is attributable largely to access to irrigation.

Household occupation, income and welfare

Information sought on the types of occupation engaged in by respondents and other household members show that for all the responding farmers, crop production activities serve as the main economic activity. However, household heads or other household members may also engage in secondary activities including livestock rearing and selling, butchering, carpentry, fishing, masonry, basketry and mat weaving, petty trading, rice and sheabutter processing, selling of scrap, wood splitting, and driving of tractor during land preparation and harvesting. Income from these activities in addition to both irrigated and non-irrigated income defines the household's total income. Further analysis on sources of household income reveals that non-farm income for respondents could be as much as 12 to 15% in the District. Thus, as much as 85 to 87% of household income is reinforced by farming income. For irrigators, average income from irrigation activity is about 45% though it could be as much as 59% at the *Bontanga* irrigation scheme. Irrigated income thus accounts for the highest proportion of total income. Higher irrigation income is augmented by higher cultivation intensity made possible by the use of purchased inputs. Analysis on the proportion of purchased inputs in total input expenditure shows that the former could be as much as 53% for irrigators and 48% for non-irrigators. A t-test result shows a significant mean difference at the 10% level. Thus increased use of purchased input is associated with irrigated production activities.

Information on household income and consumption expenditure per capita (welfare) are the following. For irrigators, a per capita income of GHc 78.7 is significantly[11] higher than that of GHc 60.2 for non-irrigators. Similarly, annual household consumption expenditure per capita in irrigating households is GHc 230.0 as against GHc 207 in non-irrigating households.

Irrigation participation model

The study analyses the impact of irrigation on household consumption per capita (welfare). It does so by utilising the PSM method to extract consistent estimates of impacts. The irrigation participation decision model has irrigation participation or membership (IRRIPA) as the binary dependent variable regressed over *ex ante* variables such as age (AGE) and years of education (YRSC) of the household head, household size (HHSI), size of farm land (SIFL), ease of access to markets (EASM), extension advice (EXT), land coverage by dam (LCOV) and nearness to scheme (NEARN).

The pseudo R-squared, which tells the explanatory power of the predictors in the model, is about 27%. The likelihood ratio chi-square value at 8° of freedom is significant at 1%. This confirms the overall fitness of the model. From the estimated parameter results, the coefficients of the square of age (AGESQ), ease of access to markets (EASM), access to extension advice (EXT) and land coverage by dam (LCOV) are significant. All four variables have positive influence on the likelihood

[9] For irrigators, a t-value of 4.923 is significant at 1% ; for non-irrigators, a t-value of 6.331 is also significant at 1%.

[10] A t-value of 2.841 is significant at 1%.

[11] A t-value of 2.580 is significant at 5%.

of participation in the irrigation project. At higher ages of household heads, a unit addition to age significantly improves the probability of participation by 0.001. This is possibly so owing to the fact that older farmers might possess richer farming experience that could be easily harnessed for improved irrigation activity. Ease of access to product markets increases the probability of participation in irrigation project by 0.164. *Ex ante* access to extension services also raises the likelihood of irrigation participation by 0.309. As known from secondary information in the study areas, victims of negative effect of dam construction are much more likely to be allocated lands than all others. The dummy variable, land coverage by dam (LCOV), shows itself as the factor influencing membership in irrigation most (0.537). A study by Adeoti et al. (2007) on adoption of treadle pumps and poverty impact in Ghana, also found extension and markets as significant determinants of *ex ante* participation in treadle pump irrigation. The buttressing outcome of their study shows the importance of access to extension and markets in the dissemination of irrigation technology.

The extraction of irrigation's impact on farm income and hence consumption expenditure per capita is therefore based on the predicted probabilities of participation (from the irrigation participation model). In this respect, for ease of demonstration but without loss of generality for the conclusions, the irrigation participation model is not specified formally in this study and the results are not presented in tabular form as usually done. However, the results are discussed briefly above.

Estimated average irrigation effect on irrigators

The average treatment effect on the treated (ATT) using nearest neighbour matching is described as follows. It follows that access to irrigation technology increases cropping intensity by 73.6% for rice, 32.1% for pepper and 33.3% for okro. With regards to crop yield[12] impacts, access to irrigation improves yield of rice by 432.4 kg/acre (1.08 t/ha) and pepper by 389.5 kg/acre (0.97 t/ha). In the presence of markets, improved yields owing to access to irrigation translate into higher incomes and hence higher household consumption expenditure per capita. Annual gross margin per acre improvements in farm income is estimated at GH₵ 88.8.

In the absence of PSM, simple difference in the means of cropping intensity, yield and income between irrigators and non-irrigators could either overestimate or underestimate the impact measure. In verifying the extent of such a bias in the study, the estimated average treatment effects on the treated is compared with estimates from simple difference in means. The biases generated from the comparison are presented. The results show that without PSM, simple mean differencing could underestimate cropping intensities of rice and okro by 3.6 and 5.2% respectively, while overestimating that of pepper by 3.2%. Similarly, rice yield could be over-estimated by 275.7 kg/acre (0.69 t/ha) and pepper yield underestimated by 0.5 kg/acre (0.001 t/ha). Gross margin per acre per year could also be overestimated by GH₵ 27.7. An overestimation arises from a positive bias because expected outcome of non-irrigators given participation (benefit) in irrigation project is higher than the expected outcome given non-participation in the project. The other way round, holds for underestimation (negative bias). Given that, non-irrigators have no physical participation in irrigation project, they may enjoy indirect benefits (spill over effects) through access to improved seed varieties (e.g. rice) and technical knowledge from their colleague irrigators, in typically homogeneous communities. The higher the benefits relative to non-participation outcome, the greater the bias, and vice versa.

The gain in yield of irrigated rice (1.1 t/ha) is found to compare well with an upper bound value of 1.5 t/ha gain in cereal yield in a study by Hussain and Hanjra (2003). Evidence of cropping intensity impacts can also be found in a 'with and without' study by Hussain and Hanjra (2003), and Hussain and Giordano (2004). Their studies show that gain in cropping intensity on irrigated settings could be in the range of 11 to 74%, which compares well with this study's (32 to 74%) for all crops. These results give credence to the fact that production-based impact of irrigation can be transmitted through a cropping intensity-yield-income channel in the *Tolon-Kumbungu* district, thereby impacting positively on household consumption expenditure per capita.

The implication of improved and stable household income as well as improved food availability due to irrigated production for household consumption expenditure per capita (welfare) is enormous. The results show that the average value of household durables for irrigators is significantly higher than non-irrigators. Thus, the acquisition of household durables positively correlates with irrigation use. Owing to the fact that irrigated income make up a substantial part of household income (30 to 59%), the former may play a substantial role in the acquisition of household durables such as radio, bicycle and motor.

The welfare-enhancing role of irrigation is also ascertained by analysing intra-household number of food deficit days averagely per week in both dry and rainy seasons as well as the months in the year households experience food shortages. The empirical results show that, the food deficit days per week in the dry season for both irrigators and non-irrigators are not significantly different from each other (1 day/week). Thus, for a day out of the whole week, both irrigating and non-irrigating households will suffer to get their normal meals, and may have to forgo it. However, in the rainy season, non-irrigating households suffer food shortages in more than 2 days. Their irrigating counterparts only experience such

[12] Secondary data show that 1bag of rice = 84kg; 1 bag of pepper = 45kg; 1 bucket of okro = 8.5kg.

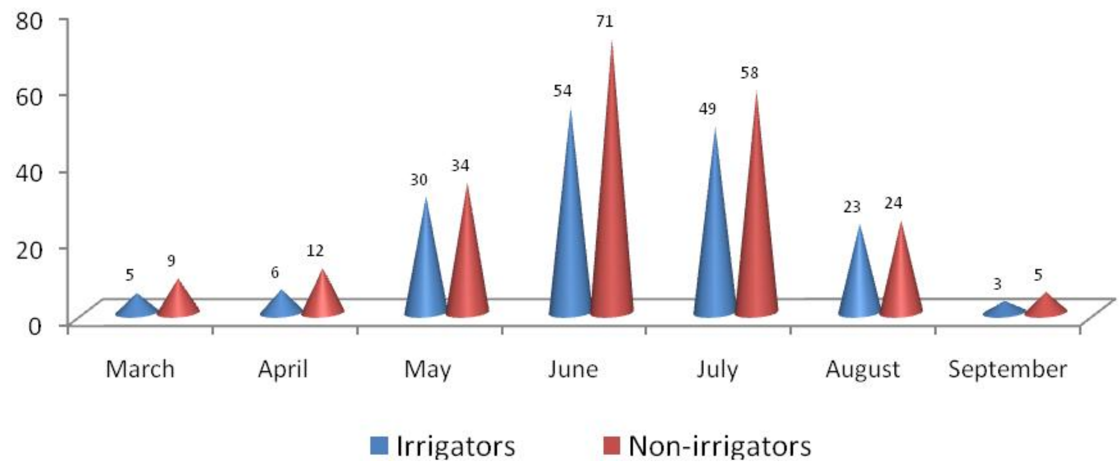

Figure 1. Months in which farmer households experience food shortages.

shortages in 1 day. From these results, it is deciphered that households suffer food deficit more in the rainy season and the intensity of the deficit is more in non-irrigating households than irrigating households. Thus non-irrigating households in the district are much welfare-constrained in the rainy season than irrigating households. This is generally seen from Figure 1, which shows the months in which households experience food shortages in the whole year. Household food shortages are concentrated between the months of May and August. The rainy season period presents much welfare problems because, in most of the areas, the unimodal rainfall regime dictates the seasonality in agricultural production activities in general. Farmers do extensive cultivation in the rainy season from May to September/October.

At the end of the rainy season as well as most parts of the dry season, farmers have enough food stuff from the season's harvest to rely on. However, at the beginning and thick of the rainy season periods, farm households already have exhausted the food stock. This reduces food availability for such house-holds, hence the deficit or shortage patterns observed. Access to irrigation water in the dry spells is therefore crucial for households in overcoming seasonality in food availability and incomes. Thus the observed less welfare-constrained irrigating households can be attributed to irrigation access and use. Irrigation is touted to make the most impact within a certain kind of environment. As highlighted from literature (Inocencio et al., 2005), in spite of irrigation being the primary trigger of impacts, good management and access to production and marketing resources are crucial for realising maximum impacts. The traces of food unavailability in some periods of the year within irrigating households cast doubts about the potency or efficiency in provision of support services in the irrigation areas. Ideal conditions should significantly improve upon welfare in irrigating households year-round.

Impact of irrigation on household consumption expenditure per capita (welfare)

The result from this model (Table 3) seems to be the best amongst the six competing specifications of the model. The adjusted R-squared shows the highest predictive power of the exogenous variables (30.66%), for a cross-sectional data of this nature. Thus close to one-third of the variation in household welfare is significantly explained by the variation in the explanatory variables, by virtue of its association with them. The value of the F-statistic (18.497) is significant at 1% showing a high fit for the model. Thus, at least one of the exogenous variables significantly explains the variation in household welfare. The irrigation dummy (IRRI) also is significant at the 1% level. Thus, irrigation significantly account for household welfare in a positive manner (0.060).

In models with mixed functional forms (variables with mixed functional relationships), the elasticities of the variables are not directly interpretable from the raw coefficient estimates. To be able to do that, further computation is necessary. Gujarati (1992) summarises a number of approaches specific to the functional relation-ship underlying the variables. From Table 3, the significant variables explaining household welfare include age of the household head, access to informal credit, access and use of irrigation technology, ease of access to markets and log of non-irrigated income per capita. The relation underlying the association between each of the first four variables and log of consumption expenditure per capita is that of Log-ln (Gujarati, 1992). The relation for the last variable is log-linear for which direct elasticity interpretation is possible. For a Log-ln relation, the elasticity is computed as the product of the average value of the explanatory variable and its marginal value. Table 4 gives the elasticities of welfare variables with respect to the significant variables in the model.

Table 3. Ordinary least squares regression (OLS) estimates of the impact of irrigation on consumption expenditure per capita (welfare).

Method: Least Squares
Included observations: 278
White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LCONSPC				
C	2.091743	0.093936	22.26778	0.0000
AGE	-0.003270	0.001067	-3.064711	0.0024***
AICRE	0.045335	0.021051	2.153557	0.0322**
IRRI	0.060132	0.019272	3.120169	0.0020***
EASM	0.041327	0.023498	1.758716	0.0798*
SCUL	-0.002571	0.002171	-1.184360	0.2373
LGLIVS	-0.015162	0.011158	-1.358818	0.1753
LGNIINCPC	0.222430	0.040738	5.460045	0.0000***
R-squared	0.324115	Mean dependent variable		2.297901
Adjusted R-squared	0.306593	S.D. dependent variable		0.179992
S.E. of regression	0.149881	Akaike info criterion		-0.929592
Sum squared residuals	6.065388	Schwarz criterion		-0.825200
Log likelihood	137.2132	F-statistic		18.49665
		Prob(F-statistic)		0.000000***

***, ** and * show significance at 1, 5 and 10% respectively. Source: survey, 2008.

From Table 4, a percentage increase in household non-irrigated income increases household welfare by 0.222%. As expected, income is a major determinant of household expenditures (Davis, 1982). An increase in the age of the household head by 1 year rather decreases household welfare by 0.168%. Access to irrigation technology improves household welfare by a margin of 0.029% compared to 0.27% increase in a study by Bhattarai and Narayanamoorthy (2003). The lower poverty elasticity of irrigation may largely be due to differing variations in the potency of the host of factors that enhance impacts (McCartney et al., 2005). The finding of Hussain (2005) is also consistent with the present results in that; just like in this study, Hussain (2005) finds irrigation as a significant positive determinant of expenditures (negative determinant of poverty). Similarly, a study by Andersson et al. (2006) finds irrigation as playing a welfare-enhancing role for lowland households but becomes welfare-constraining for households upland. The implication is that, a certain conducive environment is needed for irrigation impacts to be realised. Ease of access to markets is also found to increase household welfare by 0.026%. With regards to informal credit facility, access to such a facility enhances welfare by a margin of 0.027%.

Non-irrigated income makes the maximum contribution to household consumption expenditure per capita (welfare) followed by access to irrigation. Irrigation does not explain welfare variation as much as non-irrigated income per capita does, because of the heavy dependence of both irrigators and non-irrigators on direct consumption of expanded scale upland farm produce and incomes as compared to irrigated produce. Upland size holdings could be more than three times irrigated size holdings and output could be substantial.

The estimates of irrigation impact on household consumption expenditure per capita (welfare) by PSM estimation techniques (that is, bias-corrected estimates from all three methods) are summarised in Table 5. The magnitude of irrigation impact on household welfare from the perspective of PSM is about GH¢24.9 to GH¢28.3 per capita. Here only estimates from the stratification and nearest neighbour estimators are significant. However, the estimate from the kernel method was insignificant. It is worth nothing that these estimates are however not entirely bias-free, as unobservable biases could still be present.

The results of analysing irrigation's impact on household consumption expenditure per capita in a switching regression framework are presented in Table 6. The model very fit at the 1% level. Thus, the variation in consumption expenditure per capita is significantly explained by the variation in at least one of the independent variables. Again the independence of the regime and outcome equations is valid given the non-rejection of the alternative hypothesis of independent equations; hence a justifiable basis for sample separation. However, the correlation coefficients (ρ_j) are not significant at the conventional 10% level, meaning that an individual who chooses to be in any of the farming regimes, do no better

Table 4. Elasticities of significant variables.

Variable	Coefficient	Average value	Elasticity
AGE	-0.00327	51.52758621	-0.168
AICRE	0.045335	0.602836879	0.027
EASM	0.041327	0.617241379	0.026
IRRI	0.060132	0.482758621	0.029
LGNIINCPC	0.22243	-	0.222

Table 5. Estimates of irrigation impact (ATT) by PSM.

Variable	Matching method	No. of treatment	No. of controls	ATT	t (S.E)
Household consumption expenditure per capita(GH¢)	Stratification	140	148	24.9	1.722**(14.489)
	Nearest Neighbour	140	55	28.3	1.514*(18.719)
	Kernel	140	148	18.7	0.970(19.293)

** & * show significance at 5% and 10% levels, respectively. Figures in parenthesis are standard errors.

or worse (welfare-wise) than a random individual from the same sample will do. These findings demonstrate possible insignificant effect of unobservable factors on household consumption expenditure per capita.

The significant determinants of household consumption expenditure per capita, from the results include household dependency ratio, per capita household income, size of livestock, household head's age, extension frequency and market access. In both farming regimes, unsurprisingly, the addition of a dependant to a household significantly reduces per capita household consumption expenditure. However, the reduction in consumption expenditure as a result of a unit increase in the dependency ratio is more in non-irrigating households (GH¢14.30) than in irrigating households (GH¢5.40). This observed negative correlation between dependency ratio and consumption expenditure is consistent with the findings of Fofack (2002) and Bigsten et al. (2003), who observed negative determination of expenditures in African households. Indeed irrigation may help ameliorate the negative welfare effects of rising household dependency ratios. Similarly but positively, per capita household income significantly explains for the variation in household consumption expenditure. A cedi increase in income per capita leads to a GH¢1.30 and GH¢0.60 increase in per capita expenditures of irrigating and non-irrigating households, respectively. Irrigation's contribute-ion to household welfare is thus carried through per capita household income by way of increased farm income. Size of livestock however was only significant for irrigating households, taking a negative sign. The lower livestock holdings (average 3TLUs) of irrigators may possibly account for this realisation (Table 2). The variable household head's age is found to correlate negatively with expenditure per capita only for the non-irrigating farmers. The results show that when the head's age increases by one year, non-irrigation household expenditures reduces by GH¢2.70. This is corroborated by the findings of Asiimwe and Mpuga (2007) of the negative welfare consequences associated with ageing household heads. The two institutional variables (extension and market access) included in the model are both significant at the 1% level, but for only the non-irrigating group. These are frequency of extension services delivery and market access. Enhanced access to these support services improves household welfare by GH¢28.30 and GH¢51.50, respectively.

Predicted household expenditure per capita for irrigators (*YWirrig*) and non-irrigators (*YWnoirrig*) are presented in Table 7. Average values for the two regimes show that irrigating households have higher household consumption expenditure per capita than non-irrigating households. The magnitude of irrigation impact on household consumption expenditure per capita is estimated at GH¢23.70, which is significant at 1%.

In Table 8, impact estimates from the three main analytical methods employed in the study have been presented. Clearly the range of estimates of irrigation's impact on household consumption expenditure is positive (GH¢ 5.40 to GH¢ 28.30). Thus, the gain in household consumption expenditure per capita (GH¢) using the different methodologies are as follows: Propensity Score Matching (GH¢24.90 to GH¢28.30), Ordinary Least Squares (GH¢ 5.40), and Switching Regression (GH¢ 23.70). However, the difference in the magnitude of these estimates for each technique is ascribed to the underlying assumptions and robustness of each of these methodologies employed in the study. In the model specification for OLS regression, exogenous regressors render estimated parameters (viz. irrigation parameter) unbiased. However, under the scenario of non-random irrigation access and endogenous regressors, the presence of both observable and unobservable biases undermines the OLS regression estimate. Controlling for the observable

Table 6. Switching regression model of the impact of irrigation on consumption expenditure per capita (welfare).

	Coef.	*Std. Err.*	*z*	*p>|z|*	*[95% Conf.*	*interval]*
Conspc_1						
age	*-1.040455*	*0.754137*	*-1.47*	*0.140*	*-2.42304*	*0.342131*
yrsch	*3.723425*	*2.428748*	*1.53*	*0.125*	*-1.036834*	*8.483684*
depart	*-5.395617*	*2.639507*	*-2.04*	*0.041*	*-10.56896*	*-0.222278*
Sizlives	*-3.451156*	*1.721362*	*-2.00*	*0.045*	*-6.824963*	*-0.077349*
Sregl	*-50.03615*	*62.53433*	*-0.80*	*0.424*	*-172.6012*	*72.52889*
Sreglsq	*-20.93511*	*39.96572*	*-0.52*	*0.600*	*-99.26648*	*57.39627*
Frext	*.3040319*	*4.857929*	*0.06*	*0.950*	*-9.217333*	*9.825397*
Easm	*1.376892*	*13.07574*	*0.11*	*0.916*	*-24.25109*	*27.00487*
Incpca	*1.299856*	*0.097586*	*13.32*	*0.000*	*1.108591*	*1.491122*
_cons	*238.0603*	*43.54728*	*5.47*	*0.000*	*152.7092*	*323.4114*
conspc_0						
age	*-2.673779*	*0.946971*	*-2.82*	*0.005*	*-4.529807*	*-0.817750*
yrsch	*-3.726122*	*4.841515*	*-0.77*	*0.442*	*-13.21532*	*5.763073*
depart	*-14.34833*	*6.028058*	*-2.38*	*0.017*	*-26.1631*	*-2.533551*
Sizlives	*-0.162759*	*2.17069*	*-0.07*	*0.940*	*-4.417233*	*4.091714*
Sregl	*-17.4295*	*14.57337*	*-1.20*	*0.232*	*-45.99279*	*11.13379*
Sreglsq	*1.001636*	*1.177057*	*0.85*	*0.395*	*-1.305353*	*3.308625*
Frext	*28.29583*	*8.064421*	*3.51*	*0.000*	*12.48986*	*44.10181*
Easm	*51.4761*	*18.51212*	*2.78*	*0.005*	*15.19301*	*87.75919*
Incpca	*0.577828*	*0.341902*	*1.69*	*0.091*	*-0.092288*	*1.247944*
_cons	*336.0128*	*62.23895*	*5.40*	*0.000*	*214.0267*	*457.9989*
Irripa						
age	*-0.021477*	*0.023422*	*-0.92*	*0.359*	*-0.067383*	*0.0244284*
yrsch	*0.153855*	*0.075854*	*2.03*	*0.043*	*0.005184*	*0.3025262*
depart	*0.338528*	*0.098936*	*3.42*	*0.001*	*0.1446311*	*0.5324545*
Sizlives	*0.106954*	*0.520836*	*2.05*	*0.040*	*.0048717*	*0.2090358*
Sregl	*-4.468184*	*1.538029*	*-2.91*	*0.004*	*-7.482665*	*-1.453703*
Sreglsq	*0.284658*	*0.117751*	*2.42*	*0.016*	*0.0538694*	*0.5154462*
Frext	*0.641682*	*0.332729*	*1.93*	*0.054*	*-0.0104567*	*1.29382*
Easm	*-0.545694*	*0.299750*	*-1.82*	*0.069*	*-1.133194*	*0.041807*
Incpca	*0.018514*	*0.006526*	*2.84*	*0.005*	*0.005723*	*0.031304*
Landc	*1.903448*	*0.900115*	*2.11*	*0.034*	*0.139255*	*3.66764*
distan	*.0886413*	*0.173973*	*0.51*	*0.610*	*-0.252339*	*0.429622*
_cons	*2.020974*	*1.312643*	*1.54*	*0.124*	*-0.551759*	*4.593707*
/lns1	*4.296445*	*0.060059*	*71.54*	*0.000*	*4.17832*	*4.414158*
/lns2	*4.599193*	*0.058115*	*79.14*	*0.000*	*4.48529*	*4.713095*
/r1	*16.40356*	*350.7269*	*0.05*	*0.963*	*-671.0086*	*703.8157*
/r2	*-0.315612*	*0.461859*	*-0.68*	*0.494*	*-1.22084*	*0.589616*
sigma_1	*73.43826*	*4.410617*			*65.28301*	*82.61227*
Sigma_1	*99.40402*	*5.776814*			*88.70269*	*111.3964*
rho_1	*1*	*7.87e-12*			*-1*	*1*
rho_2	*-0.305534*	*0.418744*			*-0.839902*	*.5296192*
LR test of indep. eqns. :			*chi-square(1) = 14.48*		*prob> chi-square = 0.0001*	

Prob > chi-square = 0.0000. Endogenous switching regression model Number of obs = 288. Log likelihood = -1699.3154. Wald chi-square (9) = 276.86.

biases in a propensity score matching (PSM) framework markedly improves the impact estimate within a range of GH¢ 24.90 to GH¢ 28.30. Additional bias-correction (unobservables) of the impact estimate is attempted within

Table 7. Test of predicted welfare with endogenous switching.

	Two-sample t test with equal variances					
Variable	**Obs**	**Mean**	**Std. Err.**	**Std. Dev.**	**[95% Conf. interval]**	
Ywirrig	140	230.7583	8.407827	99.48276	214.1345	247.3821
Ywnoi~g	150	207.0845	5.56801	68.19391	196.0821	218.087
Combined	290	218.5132	5.016561	85.42896	208.6396	228.3869
diff		23.67378	9.959284		4.071564	43.27599

diff = mean(Ywirrig) - mean(Ywnoirrig) t = 2.3771

H_o: diff = 0 degrees of freedom = 288

H_a: diff < 0 H_a : diff !=0 H_a: diff >0

pr(T< t) = 0.9909 pr(ǀTǀ > ǀtǀ)=0.0181 pr(T>t) = 0.0091

Table 8. Gain in household consumption expenditure per capita (GH¢) as a result of irrigation participation

Variable	**OLS**	**PSM**	**Switching regression**
Gain in household consumption expenditure per capita (GH¢)	5.40	[24.90 , 28.30]	23.70

Gain in Per capita consumption (GH¢) for the OLS model is computed as the elasticity of the irrigation variable in the per capita consumption model multiplied by the average per capita expenditure of non-irrigating households.

an endogenous switching regression framework, yielding an estimate of GH¢ 23.70. However, the results of the switching regression framework did not indicate a significant bias from unobservable factors. The resultant estimate is therefore not significantly different from that obtained from the PSM framework. However, it comes out that the use of the OLS estimator with its underlying assumptions possibly understates the impact estimate. Robust irrigation impact estimate is adjudged to lie in the neighbourhood of GH¢ 23.70 to GH¢ 28.30.

Conclusions

This study analyses the impact of irrigation access on consumption expenditure per capita in farm households in *Tolon-Kumbungu* district in Northern Ghana. The socio-economic profile suggests that there is an ageing farmer population, with irrigation being male-dominated. Most farmers are illiterates, which has implications for interpretation, adoption and use of technical knowledge. There is an increasing size of household to date that is unrelated to access to and use of irrigation technology. Irrigators possess larger size of land holding owing to access to irrigation or membership in irrigation project. Farmer households are largely agro-based with most part of their household income on account of farm income. Irrigation income also accounts for more than half of farm income. Irrigating households enjoy higher incomes and ‘better’ welfare (household consumption per capita) than non-irrigating households. Welfare permeates in food availability, higher income and acquisition of household durables (e.g. radio, bicycle, motor).

Irrigation membership in the *Tolon-Kumbungu* district is governed by four main factors: Age (square), ease of access to markets, access to extension advice, and coverage of one’s land or livelihood by dam construction. Consistent with secondary knowledge, land coverage by dam most predict irrigation membership. Irrigation access is found to impact significantly on both production- and market-based impacts. Production-based impacts include cropping intensity and yield whiles market-based impact include income (gross margin).

This study applied a propensity score matching (PSM) approach and regression analysis (ordinary least squares and switching regression) to ascertain that, pro-poor irrigation investment in the rural savannah region of Ghana is justified due to significant irrigation contribution to consumption expenditure per capita in farm households. The results also show some differences in the impacts of irrigation access on household consumption expenditure per capita due to differences in the methodologies employed.

The impact estimates from the three main analytical methods employed in the study have been presented. Clearly the range of estimates of irrigation’s impact on household consumption expenditure is positive (GH¢ 5.40 to GH¢ 28.30). Thus, the gain in household consumption expenditure per capita (GH¢) using the different methodologies are as follows: Propensity Score Matching (GH¢24.90 to GH¢28.30), Ordinary Least Squares (GH¢ 5.40), and Switching Regression (GH¢ 23.70). However, the difference in the magnitude of these estimates for each technique is ascribed to the underlying assumptions and robustness of each of these methodologies employed in the study. In the model specification for OLS regression, exogenous regressors render estimated parameters (namely. irrigation parameter) unbiased. However, under the scenario of non-random irrigation access and endogenous regressors, the presence of both observable and unobservable biases undermines the OLS regression estimate. Controlling for the observable biases in a propensity score matching (PSM) framework markedly improves the impact estimate within a range of GH¢ 24.90 to GH¢ 28.30. Additional bias-correction (un-observables) of the impact estimate is attempted within an endogenous switching regression framework, yielding an estimate of GH¢ 23.70. However, the results of the switching regression framework did not indicate a significant bias from unobservable factors. The resultant estimate is therefore not significantly different from that obtained from the PSM framework. However, it comes out that the use of the OLS estimator with its underlying assumptions possibly understates the impact estimate. Robust irrigation impact estimate is adjudged to lie in the neighbourhood of GH¢ 23.70 to GH¢ 28.30.

A result worth noting (in the Switching Regression Model which we consider to be the most robust among the three approaches employed) is that per capita household income significantly explains for the variation in household consumption expenditure. In this respect, a cedi increase in income per capita leads to a GH¢1.30 and GH¢0.60 increase in per capita consumption expenditures of irrigating and non-irrigating households, respectively. Thus, irrigation's contribution to household welfare (That is, per capita consumption expenditures) is thus carried through per capita household income by way of increased farm income.

The contributions of this study to the existing literature are two-fold: First, the paper makes an empirical contribution by estimating the magnitude of irrigation impacts on household consumption expenditure per capita conditional on access to an irrigation facility in a developing country. The findings add to the on-going debate of the role of irrigation on welfare among farm households; second, the paper makes a theoretical contribution by comparing the magnitude of the impacts of irrigation access on household consumption expenditure per capita using different methodologies: Propensity Score Matching approach, Ordinary Least Squares Regression, and Switching Regression. In this respect, the differences in the results of the irrigation impacts on household consumption expenditure using the different approaches may be due to the underlying assumptions and the robustness of the each of these models.

The recommendations from the study are as follows: Irrigation projects in the study area indeed have welfare-enhancing roles and may have contributed to poverty reduction over the years of their existence. Pro-welfare irrigation investments in the study area are therefore justified. Efforts to rehabilitate current infrastructure and develop other dam sites in the rural savannah region should be intensified to broaden the scale of impacts.

Most formal irrigation schemes in Ghana are settlement schemes and assignment of membership to such schemes is often purposive. Objective assessment of irrigation impacts on household welfare using a 'with and without' framework must factor in the underlying process of irrigation assignment to capture consistent impacts.

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