Estimating Welfare Effect of Modern Agricultural Technologies: A Micro-Perspective from Tanzania and Ethiopia

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Abstract

Achieving agricultural growth and development and thereby improving rural household welfare will require increased efforts to provide yield enhancing and natural resources conserving technologies. Agricultural research and technological improvements are therefore crucial to increase agricultural productivity and thereby reduce poverty. However evaluation of the impact of these technologies on rural household welfare have been very limited by lack of appropriate methods and most of previous research has therefore failed to move beyond estimating economic surplus and return to research investment. This paper evaluates the potential impact of adoption of modern agricultural technologies on rural household welfare measured by crop income and consumption expenditure in rural Ethiopia and Tanzania. The study utilizes cross-sectional farm household level data collected in 2007 from a randomly selected sample of 1313 households (700 in Ethiopia and 613 in Tanzania). We estimate the casual impact of technology adoption by utilizing endogenous switching regression and propensity score matching methods to assess results robustness. This helps us estimate the true welfare effect of technology adoption by controlling for the role of selection problem on production and adoption decisions. Our analysis reveals that adoption of improved agricultural technologies has a significant positive impact on crop income although the impact on consumption expenditure is mixed. This confirms the potential direct role of technology adoption on improving rural household welfare, as higher incomes from improved technology translate into lower income poverty.

JEL classification*:* C13, C15, O32, O38

Key words: rural household welfare, technology adoption, propensity score matching, endogenous switching, Ethiopia, Tanzania

1. Introduction

In much of Sub-Saharan Africa, agriculture is a strong option for spurring growth, overcoming poverty, and enhancing food security. Of the total population of Sub-Saharan Africa in 2003, 66% lived in rural areas and more than 90% of rural people in these regions depend on agriculture for their livelihoods. Improving the productivity, profitability, and sustainability of smallholder farming is therefore the main pathway out of poverty in using agriculture for development (WDR, 2008). Achieving agricultural productivity growth will not be possible without developing and disseminating yield-increasing technologies because it is no longer possible to meet the needs of increasing numbers of people by expanding areas under cultivation. Agricultural research and technological improvements are therefore crucial to increase agricultural productivity and thereby reduce poverty and meet demands for food without irreversible degradation of the natural resource base.

Agricultural research can contribute to poverty reduction in three major ways. First, agricultural research helps in developing yield-increasing technologies contributing to an increase in the supply of food on which the poor spend a considerable share of their income. The development of high-yielding varieties, which boost food production both by increasing yields per unit of land per cropping season and by facilitating multiple cropping, must remain a critical component of the research strategy to achieve first Millennium Development Goal (MDG 1) of halving poverty by 2015. Second, agricultural research help to conserve natural resources since the poor lack alternative means to intensify agriculture except forced to overuse or misuse the natural resource bases to meet basic needs. Third, because the poor tend to reside in unfavoured or marginal agricultural areas, research should aim at developing technologies suitable for these. However, it is widely argued that research often neglected the unfavoured areas, thereby worsening poverty in them by reducing market prices of grains without improving technology (Lipton and Longhurst, 1989). The question remains, however, as to what types of technology are suitable for marginal areas. What kinds of research have high expected payoffs in terms of income generation and, hence, poverty reduction in such areas?

In the face of increasing variability of economic and agro-climatic conditions in the semi-arid tropical countries in Africa, dryland legumes like chickpea, pigeonpea and peanuts presents an opportunity in reversing the trends in productivity, poverty and food insecurity. In part, this is because legumes have the capacity to fix atmospheric nitrogen in soils and thus improves soil fertility and save fertilizer costs in subsequent crops. Second, it improves more intensive and productive use of land, particularly in areas where land is scarce and the crop can be grown as a second crop using residual moisture. Third, it reduces malnutrition and improves human health especially for the poor who cannot afford livestock products. Fourth, the growing demand in both the domestic and export markets provides a source of cash for smallholder producers.

Despite the crucial role of dryland legumes for poverty reduction and food security in semi-arid tropics, lack of technological change and market imperfections have often locked small producers into subsistence production and contributed to stagnation of the sector (Shiferaw and Teklewold, 2007). Often the traditional variety dominates the local and export markets, however; low productivity of the variety limits the farmers' competitiveness in these markets. To harness the untapped potential of legumes for the poor, the national agricultural research organization of Ethiopia in collaboration with International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) have developed and released several high-yielding and stress tolerant varieties of chickpea with desirable agronomic and market traits. A total of 11 improved chickpea varieties had been released as a result of this research program. In Tanzania, a screening program for fusarium resistance was initiated as a concerted effort between ICRISAT and Tanzania researchers in the early 1990s. The main trust was to identify disease resistant types that combine market and farmer-preferred traits. This effort resulted in development of two fusarium-resistant improved pigeonpea among 21 varieties that were successfully tested on station, which are becoming popular in Tanzania (Shiferaw *et al*., 2008).

The underlying objectives of such undertakings are to reduce hunger, malnutrition, poverty and increase the incomes of poor people living in drought-prone areas of Sub-Saharan Africa. However, evaluating of the impact of these improved technologies on household welfare outcomes have been very limited by lack of appropriate methods and most of previous research has therefore failed to move beyond estimating economic surplus and return to research investment. Thus using farm-level data collected from a random cross-section sample of 1313 small-scale producers (700 in Ethiopia and 613 in Tanzania), the objective of this paper is to provide rigorous empirical evidence on the role of improved chickpea and pigeonpea technology adoption on household welfare outcomes measured by crop income and consumption expenditure in rural Ethiopia and Tanzania.

From an econometric standpoint analyzing the welfare implications of agricultural technology poses at least two challenges: unobserved heterogeneity and possible endogeneity. There seems to be a two-way link between technology adoption and household well-being. Technology adoption may result in productivity enhancement for small producers and greater income, but it may also be that greater income leads to more technology adoption. In this paper, we take into account that the differences in welfare outcome variables between those farm households that did and those that did not adopt improved technology could be due to unobserved heterogeneity. Not distinguishing between the casual effect of technology adoption and the effect of unobserved heterogeneity could, indeed, lead to misleading policy implications. We account for the endogeneity of the adoption decision (that is, for the heterogeneity in the decision to adopt or not to adopt new technology and for unobservable characteristics of farmers and their farm) by estimating a simultaneous equations model with endogenous switching by full information maximum likelihood estimation. We also employed non-parametric regression method (propensity score matching) to assess the robustness of the results.

This paper aims to contribute to the literature by providing a micro perspective on the impact of agricultural technology. Assessing the impact of farm technology adoption can assist with setting priorities, providing feedback to the research programs, guide policy makers and those involved in technology transfer to have a better understanding of the way new technologies are assimilated and diffused into farming communities, and show evidence that clients benefit from the research products (Manyong *et al*., 2001). Now days there is clear demand for greater institutionalization of impact assessment and impact culture with a better understanding of the complexities of the links between agricultural technology and poverty.

The remainder of the paper is organized as follows. Section two present the survey design and data. Section three shows the econometric model used for estimation. Section four presents the estimation results and in section five conclusions are drawn and some further implications are noted.

2. Survey Design and Data

The data used for this paper originates from a survey conducted by the International Crop Research Institute for Semi-Arid Tropics (ICRISAT), Ethiopian Institute of Agricultural Research (EIAR) and Selian Agricultural Research Institute (SARI). The primary survey was done in two stages. First, a reconnaissance survey was conducted by a team of scientists to have a broader understanding of the production and marketing conditions in the survey areas. During this exploratory survey, discussions were held with different stakeholders including farmers, traders and extension staff working directly with farmers. The findings from this stage were used to refine the study objectives, sampling methods and the survey instrument. The household survey was then carried out in March 2008 in Ethiopia and from October to December 2008 in Tanzania. A formal survey instrument was prepared and trained enumerators collected the information from the households via personal interviews.

A multi-stage sampling procedure was used to select districts, *kebeles*[1] and farm households. In the first stage, three districts namely Minjar-Shenkora, Gimbichu and Lume-Ejere were purposively selected from the major legume producing area based on the intensity of chickpea production, agro-ecology and accessibility. These districts represent one of the major chickpea growing areas in the country where improved varieties are beginning to be adopted by farmers. The districts are in the Shewa region in the central highlands of the country and are located north east of Debre Zeit which is 50 kms south east of the capital, Addis Ababa. Debre Zeit Agricultural Research Centre (DZARC) is also located in the area and is a big asset to the districts in terms of information on quality seed, agronomic practices, marketing, storage, introducing new crop varieties and other relevant information. Chickpea production in Gimbichu and Lume-Ejere districts ranges from 12,500 to 15,000 ha whereas chickpea production in Minjar-Shenkora ranges from 15,000 to 17,500 ha per year. The crop is grown during the post-rainy season on black soils using residual moisture.

A random sample of 8-10 *kebeles* growing chickpea were selected from each district for the survey. This was followed by random sampling of 150-300 farm households from each district. A slightly higher sample was taken from Lume-Ejere district mainly because of large number of households growing chickpea in this district.

In Tanzania, the sampling framework is based on a multi-stage random sample of villages in four districts in the Northern zone of Tanzania. In the first stage, four districts namely Babati, Kondoa, Arumeru and Karatu were selected from the major legumes producing area based on the intensity of pigeonpea production, agro-ecology and accessibility. These districts represent one of the major pigeonpea growing areas in the country where improved

[1] This refers to peasant associations (rural communities) which represent the lowest administrative unit in the country.

varieties are beginning to be adopted by farmers. In each of the four districts three major divisions were selected giving rise to a total of 12 divisions. Subsequently, two wards were sampled in each of the selected divisions resulting into a total of 24 wards. Twenty five farmers were then randomly sampled from a list of farm families in each village and ward. A total of 613 farm households in four districts were surveyed using the standardized survey instrument.

The survey collected valuable information on several factors including household composition and characteristics, land and non-land farm assets, livestock ownership, household membership in different rural institutions, varieties and area planted, costs of production, yield data for different crop types, indicators of access to infrastructure, household market participation, household income sources and major consumption expenses.

3. Empirical impact evaluation challenges and estimation strategies

3.1 Impact evaluation problem

Estimation of the welfare gain of adoption of agricultural technologies based on non-experimental observations is not trivial because of the need of finding on counterfactual of intervention. What we cannot observe is the welfare outcome for those farmers who adopted improved technology had they not had adopted it (or the converse). In experimental studies, this problem is addressed by randomly assigning improved seeds to treatment and control status, which assures that the welfare outcome observed on the control households that adopt improved technology are statistically representative of what would have occurred without adoption. However, improved technology is not randomly distributed to the two groups of the households (adopters and non-adopters), but rather the households themselves deciding to adopt or not to adopt based on the information they have. Therefore, adopters and non-adopters may be systematically different.

The simplest approach to examine the impact of adoption of improved technologies on welfare outcomes would be to include on welfare equation a dummy variable equal to one if the farm-household adopted new technology, and then, to apply ordinary least squares. This approach, however, might yield to biased estimates because it assumes that adoption of improved technology is exogenously determined while it is potentially endogenous. The decision to adopt or not is voluntary and may be based on individual self-selection. Farmers that adopted may have systematically different characteristics from the farmers that did not adopt, and they may have decided to adopt based on expected benefits. Unobservable characteristics of farmer and their farm may affect both the adoption decision and the welfare outcome, resulting in inconsistent estimates of the effect of adoption of agricultural technology on household welfare. For instance, if only the most skilled or motivated farmers choose to adopt and we fail to control for skills, then we will incur in an upward bias. The solution is to explicitly account for such endogeneity using simultaneous equation models (Hausman, 1978).

The other econometric issue is that even if we account for the endogeneity, it may be inappropriate to use a pooled sample of adopters and non-adopters (i.e. a dummy regression model wherein a binary indicator is used to assess the effect of chickpea/pigeonpea technology adoption on some welfare outcome variables). The question is whether technology adoption should be assumed to have an average impact over the entire sample of farmers, by way of an intercept shift, or it should be assumed to raise the productivity of factors of production, by way of slope shifts in the income function (Alene and Manyong, 2007). Pooled model estimation assumes that the set of covariates has the same impact on adopters and non-adopters (i.e. common slope coefficients for both regimes). This implies that technology adoption has only an intercept shift effect, which is always the same irrespective of the values taken by other covariates that determine welfare outcome. If it is assumed that factors of production have differential effects on household welfare outcome, separate welfare outcome functions for adopters and non-adopters have to be specified, while at the same time accounting for endogeneity. The econometric problem will thus involve both endogeneity (Hausman 1978) and sample selection (Heckman 1979). This motivates an endogenous switching regression model that accounts for both endogeneity and sample selection and allows interactions between adoption and other covariates in the welfare outcome function (Freeman *et al*., 2001 and Alene and Manyong, 2007). Two proxies are used to measure household welfare outcome in this paper, namely crop income and household consumption expenditure per adult equivalent[2]. Thus we estimate two welfare outcome functions for adopters and another for non-adopters. In addition to switching regression, we also employed non-parametric techniques, namely propensity score matching (PSM), to overcome the econometric problems and assess the robustness of our results.

[2] Income from crop production is calculated as annual production value of farm products minus paid-out costs, which include costs on seeds, fertilizer, chemicals, hired labor and oxen rental including own oxen. Consumption expenditures captures six major categories including food grains, livestock product (such as meat), vegetables and other food items (such as sugar, salt), beverages (such as coffee, tea leaves), clothing and energy (such as shoes, kerosene) and social activities (contribution to churches or local organization, education and medical expenditure) over the twelve months (2006/07).

3.2 Propensity score matching (PSM) methods

The propensity score matching method is one of the non-parametric estimation techniques that do not depend on functional form and distributional assumptions. The method is intuitively attractive as it helps in comparing the observed outcomes of technology adopters with the outcomes of counterfactual non-adopters (Heckman *et al*., 1998). Despite its heavy data requirements, the matching method can produce experimental treatment effect results when such data are not feasible and/or available. It also helps to evaluate programs that require longitudinal datasets using single cross-sectional dataset where the former does not exist. The basic idea of the PSM method is to match observations of adopters and non-adopters according to the predicted propensity of adopting a superior technology (Rosebaum and Rubin 1983: Heckman *et al*., 1998; Smith and Todd, 2005; Wooldridge, 2005). The main feature of the matching procedure is the creation of the conditions of randomized experiment in order to evaluate a causal effect as in a controlled experiment.

Let G_i denotes a dummy variable such that $G_i = 1$ if the i^{th} individual adopt improved technology and $G_i = 0$ otherwise. Similarly let Y_{1i} *and* Y_{2i} denote potential observed welfare outcomes for adopter and non-adopter units respectively. Then $\Delta = Y_{1i} - Y_{2i}$ is the impact of the technology on the i^{th} individual, usually called treatment effect. As we observe $Y_i = G_i Y_{1i} + (1 - G_i) Y_{2i}$ rather than Y_{1i} *and* Y_{2i} for the same individual, we are unable to compute the treatment effect for every unit. The primary treatment effect of interest that can be estimated is therefore the Average impact of Treatment on the Treated (ATT) given by

$$\tau = E(Y_{1i} - Y_{2i} / G_i = 1) \tag{1}$$

Following Rosenbaum & Rubin (1983), the propensity score can be estimated as

$$P(X) = P(G_i = 1 / X) \tag{2}$$

Given the assumptions that (a) $Y_{1i}, Y_{2i} \perp G / X$ i.e., the potential outcomes are independent of technology adoption given X, this imply $E(Y_{2i} / G = 1, P(X)) = E(Y_{2i} / G = 0, P(X))$ and (b) $0 < P(X) < 1$,i.e., for all X there is a positive probability of either adopting $(G = 1)$ or not adopting $(G = 0)$, this guarantees every adopter a counterpart in the non-adopter population, The ATT can then be estimated as

$$\begin{aligned}\tau &= E(Y_{1i} - Y_{2i} / G_i = 1) \\ &= E\left[E(Y_{1i} - Y_{2i} / G_i = 1, P(X))\right] \\ &= E\left[E(Y_{1i} / G_i = 1, P(X)) - E(Y_{2i} / G_i = 0, P(X))\right]\end{aligned} \tag{3}$$

The propensity score is a continuous variable and there is no way to get adopter with the same score as its counterfactual(s). Thus, estimation of the propensity score is not sufficient to compute the average treatment effect given by equation (3). We need to search for counterfactual(s) that matches with each adopter depending on its propensity score. Different matching methods are used in the literature (for detail explanations refer Smith and Todd, 2005). We use the nearest-neighbor matching method to pick comparison groups. This method could use a single nearest-neighbor or multiple nearest-neighbors with the closest propensity score to the corresponding adopter unit. The method could also be applied with or without replacement where the former allows a given non-adopter to match with more than one adopter (Becker and Ichino, 2002; Dehejia and Wahba, 2002). To check the robustness of our result, the impact estimate calculated using the nearest neighbor matching method is compared to the estimates of Kernel matching method. As discussed earlier, the observed outcome variable used as a proxy for the welfare of smallholder farmers, in this paper, are crop income and household consumption expenditure per adult equivalent.

3.3 Endogenous switching regression models

To complement the PSM techniques and to assess consistency of the results to different assumptions, endogenous switching regression techniques were applied[3]. We specify the selection equation for technology adoption as

$$G_i^* = \beta X_i + u_i \text{ with } G_i = \begin{cases} 1 & if\ G_i^* > 1 \\ 0 & otherwise \end{cases} \tag{4}$$

where G_i^* is the unobservable or latent variable for technology adoption, G_i is its observable counterpart (the dependent variable adoption of improved chickpea/pigeonpea varieties equals

[3] Propensity score methods are not consistent estimators in the presence of hidden bias, however instrumental variables estimation can provide consistent estimation of causal effects even in the presence of hidden bias. We are not taking a stand on what is the correct assumption regarding unobservables and we will present all sets of estimates.

one, if the farmer has adopted at least one improved chickpea/pigeonpea varieties during 2006/07 cropping season, and zero otherwise), X_i are non-stochastic vectors of observed farm and non-farm characteristics determining adoption and u_i is random disturbances associated with the adoption of improved technology.

Adoption decisions of the farmer are assumed to be derived from the maximization of a discounted expected utility of farm profit subjected to imperfect or missing factor market for land, labor, credit and perception of farm households. In situations where input and output markets are missing or imperfect, the level of wealth affects production activities of the households. Human capital variables and/or household specific characteristics like family labor force, education level of household head, age and gender of the household head were also included. Contact with government and non-government extension agents and access to off-farm actives were also included as explanatory variables in the model. We expect these variables to explain the farmer's awareness about the advantages of the new varieties and hence positively affect the level of adoption. We also include variables capturing access and information such as credit, seed, media, group membership, off-farm etc. Specific context and location variables like distance from main market and district dummies were also included in the model. Distance from main market can proxy transaction costs associated with marketing of the farmers' agricultural inputs and is expected to negatively influence the level of adoption. Dummy variables for the districts were also used to capture infrastructure, remoteness, rainfall variation and other geographical variations across regions.

To account for selection biases we adopt an endogenous switching regression model of welfare outcomes, (i.e. crop income and consumption expenditure per capita) where farmers face two regimes (1) to adopt, and (2) not to adopt defined as follows:

Regime 1: $Y_{1i} = \alpha J_{1i} + e_{1i} \text{ if } G_i = 1$ (5a)

Regime 2: $Y_{2i} = \alpha_2 J_{2i} + e_{2i} \text{ if } G_i = 0$ (5b)

Where Y_i is crop income and household consumption expenditure per adult equivalent in regimes 1 and 2, J_i represent a vector of exogenous variables thought to influence crop income and consumption expenditure.

Finally, the error terms are assumed to have a trivariate normal distribution, with zero mean and non-singular covariance matrix expressed as

$$\operatorname{cov}(e_{1i}, e_{2i}, u_i) = \begin{pmatrix} \sigma_{e2}^2 & . & \sigma_{e2u} \\ . & \sigma_{e1}^2 & \sigma_{e1u} \\ . & . & \sigma_u^2 \end{pmatrix} \tag{6}$$

where σ_u^2 is the variance of the error term in the selection equation (4), (which can be assumed to be equal to 1 since the coefficients are estimable only up to a scale factor), σ_{e1}^2 and σ_{e2}^2 are the variances of the error terms in the welfare outcome functions (5a) and (5b), and σ_{e1u} and σ_{e2u} represent the covariance of u_i e_{1i} and e_{2i}. Since Y_{1i} and Y_{2i} are not observed simultaneously the covariance between e_{1i} and e_{2i} is not defined (Maddala, 1983). An important implication of the error structure is that because the error term of the selection equation (4) u_i is correlated with the error terms of the welfare outcome functions (5a) and (5b) (e_{1i} and e_{2i}), the expected values of e_{1i} and e_{2i} conditional on the sample selection are nonzero:

$$E[e_{1i}/G_i = 1] = \sigma_{e1u}\frac{\phi(\beta X_i)}{\Phi(\beta X_i)} = \sigma_{e1u}\lambda_{1i,}\ and\ E[e_{2i}/G_i = 0] = -\sigma_{e2u}\frac{\phi(\beta X_i)}{1-\Phi(\beta X_i)} = \sigma_{e2u}\lambda_{2i}$$

where ϕ (.) is the standard normal probability density function, Φ (.) the standard normal cumulative density function, and $\lambda_{1i} = \frac{\phi(\beta X_i)}{\Phi(\beta X_i)}$, and $\lambda_{2i} = -\frac{\phi(\beta X_i)}{1-\Phi(\beta X_i)}$. If the estimated covariances σ_{e1u} and σ_{e2u} are statistically significant, then the decision to adapt and the welfare outcome variables are correlated, that is we find evidence of endogenous switching and reject the null hypothesis of absence of sample selectivity bias. This model is defined as a "switching regression model with endogenous switching" (Maddala and Nelson, 1975).

An efficient method to estimate endogenous switching regression models is by full information maximum likelihood (FIML) estimation (Lee and Trost, 1978; Lokshin and Sajaia, 2004).[4] The FIML method simultaneously estimates the probit criterion or selection equation

[4] An alternative estimation method is the two-step procedure (see Maddala, 1983, for details). However, this method is less efficient than FIML, it requires some adjustments to derive consistent standard errors (Maddala, 1983), and it shows poor performance in case of high multicollinearity between the covariates of the selection

and the regression equations to yield consistent standard errors. Given the assumption of trivariate normal distribution for the error terms, the logarithmic likelihood function for the system of equations (4) and (5a &5b) can be given as

$$LnL_i = \sum_{i=1}^{N} G_i \left[\ln \phi \left\langle \frac{e_{1i}}{\sigma_{e1}} \right\rangle - \ln \sigma_{e1} + \ln \Phi(\varphi_{1i}) \right] + (1 - G_i) \left[\ln \phi \left\langle \frac{e_{2i}}{\sigma_{e2}} \right\rangle - \ln \sigma_{e2} + \ln(1 - \Phi(\varphi_{2i})) \right] \tag{7}$$

Where $\varphi_{ji} = \frac{(\beta X_i + \gamma_j e_{ji} / \sigma_j)}{\sqrt{1-\gamma_j^2}}$, $j_i = 1, 2, with\ \sigma_j$ denoting the correlation coefficient between the error term u_i of the selection equation (4) and the error term e_{ij} of equation (5a) and (5b), respectively. The FIML estimates of the parameters of the endogenous switching regression model can be obtained using the *movestay* command in STATA (Lokshin and Sajaia 2004).

In addition, for identification purposes, we followed the usual order condition that X_i contains at least one element not in J_i imposing an exclusion restriction on Equation (7). These variables do not have any direct effect on the crop income and consumption expenditure, although they are hypothesised to affect the probability that the household adopts improved technology.

3.4 Conditional expectations, treatment and heterogeneity effects

The aforementioned endogenous switching regression model can be used to compare the expected crop income and consumption expenditure of the farm households that adopted (a) with respect to the farm households that did not adopt (b), and to investigate the expected income and consumption expenditure in the counterfactual hypothetical cases (c) that the adopted farm households did not adopt, and (d) that the non-adopters farm households adopted. The conditional expectations for our outcome variables in the four cases are presented in table 1 and defined as follows

$$E(Y_{1i} / G_i = 1) = \alpha_1 J_{1i} + \sigma_{e1u} \lambda_{1i} \tag{8a}$$

$$E(Y_{2i} / G_i = 0) = \alpha_2 J_{2i} + \sigma_{e2u} \lambda_{2i} \tag{8b}$$

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equation (4) and the covariates of the welfare outcome equations (5a) and (5b) (Hartman, 1991; Nelson, 1984; and Nawata, 1994).

$$E(Y_{2i} / G_i = 1) = \alpha_1 J_{1i} + \sigma_{e2u} \lambda_{1i} \tag{8c}$$

$$E(Y_{1i} / G_i = 0) = \alpha_2 J_{1i} + \sigma_{e1u} \lambda_{2i} \tag{8d}$$

< TABLE 1 ABOUT HERE>

Cases (a) and (b) along the diagonal of table 1 represent the actual expectations observed in the sample. Cases (c) and (d) represent the counterfactual expected outcomes. In addition, following Heckman *et al*. (2001), we calculate the effect of the treatment 'to adopt' on the treated (TT) as the difference between (a) and (c)

$$E(Y_{1i} / G_i = 1) - E(Y_{2i} / G_i = 1) = J_{1i}(\alpha_1 - \alpha_2) + \lambda_{1i}(\sigma_{e1u} - \sigma_{e2u}) = TT \tag{9}$$

which represents the effect of improved agricultural technology on the crop income and consumption expenditure of the farm households that actually adopted the technology. Similarly, we calculate the effect of the treatment of the untreated (TU) for the farm households that actually did not adopt improved agricultural technologies as the deference between (d) and (b),

$$E(Y_{1i} / G_i = 0) - E(Y_{2i} / G_i = 0) = J_{2i}(\alpha_1 - \alpha_2) + \lambda_{2i}(\sigma_{e1u} - \sigma_{e2u}) = TU \tag{10}$$

We can use the expected outcomes described in (4a)-(4d) to calculate the heterogeneity effects. For example, farm households that adopted improved technologies may have earned more income and spend on consumption than farm households that did not adopt regardless of the fact that they decided to adopt but because of unobservable characteristics such as their skills. Adapting Carter and Milon (2005) to our case, we define as "the effect of base heterogeneity" for the group of farm households that decided to adopt as the difference between (a) and (d),

$$E(Y_{1i} / G_i = 1) - E(Y_{1i} / G_i = 0) = \alpha_{1i}(J_{1i} - J_{2i}) + \sigma_{e1u}(\lambda_{1i} - \lambda_{2i}) = BH_1 \tag{11}$$

Similarly for the group of farm households that decided not to adopt, "the effect of base heterogeneity" is the difference between (c) and (b)

$$E(Y_{2i} / G_i = 1) - E(Y_{2i} / G_i = 0) = \alpha_{2i}(J_{1i} - J_{2i}) + \sigma_{e2u}(\lambda_{1i} - \lambda_{2i}) = BH_2 \tag{12}$$

Finally, we investigate the "transitional heterogeneity" (TH), that is if the effect of adopting improved agricultural technology is larger or smaller for the farm households that actually adopted the technologies or for the farm household that actually did not adopt in the counterfactual case that they did adopt, that is the difference between equations (9) and (10) (i.e., (TT) and (TU)).

4. Results and discussion

The data analysis is performed in two steps. In the first section, a description of the socioeconomic characteristics of the sample households comparing adopters and non-adopters for both Tanzania and Ethiopia is presented. In the second section, we present the econometric results on the role of improved chickpea and pigeonpea technology adoption on household welfare outcomes in rural Ethiopia and Tanzania.

4.1 Descriptive statistics

Table 2 presents the t-test and chi-square comparison of means of selected variables by adoption status for the surveyed 700 households in Ethiopia and 613 households in Tanzania. Some of these characteristics are the explanatory variables of the estimated models we present further on.

The Ethiopian dataset contains 700 farm households and of these, about 32% are adopters i.e. planted at least one of the improved chickpea varieties during 2006/07 cropping season. The area planted of improved chickpea varieties is about 0.6 ha for adopters. Average age of sample household head is about 47 years and about 9% are female-headed. No significant difference is observable in the age and gender of the household head although the groups vary in terms of their marital status. Adopter categories do not seem to significantly vary in terms of primary and junior level of education (1 to 8 years) however adopters have higher proportion of household heads with secondary education. This suggests that education might be uncorrelated with decision to adopt. The average active family labor force is 3.7 persons for adopters and 3.4 for non-adopters and the difference is statistically significant supporting the importance of family labor for adoption of new technologies. The adopter groups are distinguishable in terms of asset holding whereby adopters own more livestock per capita, land per capita and farm asset per capita. No significant difference is observable in access to off-farm activities and practicing water conservation and soil fertility.

Average walking distance to the main market is significantly lower for adopters and they seem to have also more access to extension service, media service and official positions. However, there is no significant difference in terms of household membership in different rural institutions. The result also depicts that the adopter categories are distinguishable in terms of their knowledge of the existing improved chickpea varieties and perception about those varieties. Adopters have more experience in chickpea farming as well as farmer to farmer seed exchange. This simple comparison of the two groups of smallholders suggests that adopters and non-adopters differ significantly in some proxies of physical, human and social capital.

< TABLE 2 ABOUT HERE>

The Tanzanian dataset contains 613 farm households and of these, about 33% are adopters i.e. planted at least one of the improved pigeonpea varieties during 2006/07 cropping season. Results show that improved pigeonpea adopter categories are distinguishable in terms of household characteristics such as household head year of schooling. The level of education of the household head is significantly higher for improved pigeonpea adopters. No significant difference is observable in the age of the household head. Similarly, adopter categories are distinguishable in terms of proxies of asset holding such as non-oxen asset and rented-in land size perhaps due to farmers who rented in land to reap the benefit by adopting farm technology. Improved pigeonpea adopters are also distinct in terms of access indicators to extension service as indicated by number of farmer's contact with government and non-government extension agents. Adopters are also more likely to have access to information related with farm technology, and experience in technology evaluation or transfer. Moreover the adopter categories tend to vary significantly in terms of their membership in a community or farmer groups; the share of households with farmer group membership is significantly higher for pigeonpea adopters.

The adopter groups are also significantly distinguishable in terms of welfare, measured by livestock income, off-farm income, crop income and consumption per adult equivalent. Off-farm and crop income per adult equivalent is significantly higher for improved pigeonpea adopters compared to the non-adopters counterparts. There is also a significant difference in terms of livestock income per adult equivalent between pigeonpea adopter categories. As far as crop income and consumption expenditure per adult equivalent is concerned, pigeonpea adopter categories are distinguishable in crop income while it is not the case for consumption.

In the subsequent part of the chapter, a rigorous analytical model is estimated to verify whether these differences in mean crop income and consumption per adult equivalent remain unchanged after controlling for all confounding factors. To measure the impact of adoption, it is necessary to take into account the fact that individuals who adopt improved varieties might have achieved a higher level of crop income and consumption even if they had not adopted.

4.2 Econometric results

The correlation between adoption of improved farm technology and household welfare outcomes such as consumption and income is theoretically complex and there are further empirical pitfalls regarding the impact evaluation problem. We estimated the consumption and income effect of a superior farming technology based on cross-sectional data available. First we used propensity score matching fowling by endogenous switching regression model to address the research questions.

Table 3 report the estimation results for the average treatment effect on the treated (ATT) of the outcome variable using PSM techniques. In our application of PSM, we first estimate a probit regression in which the dependent variable equals one if the household adopted at least one improved technology, zero otherwise. We then check the balancing properties of the propensity scores. The balancing procedure tests whether or not adopters and non-adopters observations have the same distribution of propensity scores[5]. When balancing test failed, we tried alternative specifications of the probit model; the specification used in this paper is the most complete and robust specifications that satisfied the balancing tests[6]. The quality of the match can be improved by ensuring that matches are formed only when the distribution of the density of the propensity scores overlaps adopters and non-adopters observations—that is, when the propensity score densities have "common support." For this reason, we used the common support approach for all PSM estimates. For the common support sample, the probit model was estimated again to obtain a new set of propensity scores to be used in creating the match. We also retested the balancing properties of the data. All results presented in the following pages are based on specifications that passed the balancing tests. We matched adopters and non-adopters observations by two PSM techniques as discussed earlier. The standard errors of the impact estimates are calculated by bootstrap using 100 replications for each estimate.

The estimated results based on the two matching algorithms, the Kernel method (KM) and nearest neighborhood (NNM), are reported in table 3. Our analysis reveals that adoption of

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[5] A balancing test fails when a *t*-test rejects the equality of the means of these variables across ranked groupings of the propensity score.

[6] Results of balancing test are not reported here but are available on request.

improved agricultural technologies has a significant positive impact on crop income although the impact on consumption expenditure is mixed. For Ethiopia, the overall average gain of adopting improved chickpea technologies in crop income per adult equivalent ranges from 0.29 to 0.11. The estimated gain was statistically significant at 90% confidence level for NN matching while it is not significant for KM method. For Tanzania, both KM and NNM estimates show a positive and statistically significant impact of adoption of improved pigeonpea technologies on crop income per adult equivalent. Adoption of improved pigeonpea had raised the crop income by about 98% for NNM and 71% for KM on average compared to the non-adopters. It is the average difference between crop incomes of similar pairs of the households belonging to the non-adopters. This indicates that (assuming there is no selection bias due to unobservable factors) crop income per adult equivalent for farmers who adopted improved chickpea and pigeonpea varieties is significantly higher than the non adopters.

< TABLE 3 ABOUT HERE>

Results for the casual impact of adoption of improved agricultural technologies on consumption expenditure are mixed. For Ethiopia, the overall average gain of adopting improved chickpea technologies in consumption expenditure per adult equivalent ranges from 0.04 for NNM to 0.07 for KM but the result is only significant for the later one. For Tanzania, adoption of improved pigeonpea technologies had no significance impact on consumption expenditure per adult equivalent. The PSM results do not show strong evidence concerning the positive causality between adoption of improved technologies and consumption expenditure. This perhaps may be because of the consumption behavior of the household that in the short run farmers may not adjust immediately with income. But also it may be because PSM cannot provide consistent estimation of causal effects in the presence of hidden bias.

To check the robustness of our PSM findings, we estimated endogenous switching regression that can control for unobservable selection bias. The full information maximum likelihood estimates of the endogenous switching regression model are reported in table 4a and 4b for pigeonpea adoption in Tanzania[7]. The first column presents the estimated coefficients of selection equation (4) on adopting improved pigeonpea or not whereas the second and third column presents the consumption expenditure and crop income functions (5a) and (5b) for

[7] The full information maximum likelihood estimates of the endogenous switching regression model are not reported for chickpea adoption in Ethiopia and can be available on request. Determinates of consumption expenditure and crop income are also not discussed since it is not the primary objective of the paper.

farm households that did and did not adopt improved pigeonpea technology. To analyze the correlates of crop income and consumption expenditure per adult equivalent, we include a broad set of explanatory variables including household demographic factors, specific individual/household head characteristics, asset holdings, district level factors, and policy related variables. Results from the endogenous switching regression model estimated by full information maximum likelihood shows that the estimated coefficient of correlation between the pigeonpea adoption equation and the consumption expenditure function (φ_j) is negative and significantly different from zero. The results suggest that both observed and unobserved factors influence the decision to adopt modern agricultural technology and welfare outcomes given the adoption decision. The significance of the coefficient of correlation between the adoption equation and the welfare of adopters indicates that self-selection occurred in the adoption of improved agricultural technologies. The differences in the consumption expenditure equation coefficient between the farm households that adopted improved pigeonpea and that did not illustrate the presence of heterogeneity in the sample (Table 4, column 2 and 3). The consumption expenditure function of farm households that adopted improved pigeonpea is significantly different (at the 1 percent level) from the consumption function of the farm household that did not adopt.

< TABLE 4 ABOUT HERE>

Table 5 presents the expected household welfare outcome (i.e. crop income and consumption expenditure) under actual and counterfactual conditions for Tanzania. The predicted crop-incomes and consumption per adult equivalent from endogenous switching regression model are used to examine the mean crop-incomes and consumption expenditure gap between adopters and had they not been adopt. Cell (a) and (b) represent the expected crop income and consumption expenditure per adult equivalent observed in the sample. The expected crop income per adult equivalent by farm households that adopted is higher than the group of households that did not adopt. This simple comparison, however, can be misleading and drive the researcher to conclude that on average the farm households that adopted improved technology earned more than the farm households that did not adopt.

< TABLE 5 ABOUT HERE>

The last column of table 5 presents the treatment effects of adoption of pigeonpea. The result from the regression indicates that the mean value of crop income per adult equivalent of pigeonpea adoption is statistically higher than had they not been adopt. This is consistent with the result from propensity score matching. Improved pigeonpea adoption increases crop-incomes per adult equivalent by about 109%. For non-adopters the mean crop income per adult equivalent would have been increased by 44% had they adopted improved pigeonpea.

Unlike to PSM results which compares the treated and control based on observable variables, the result from switching regression confirms that adoption of pigeonpea have also a positive impact on consumption expenditure per adult equivalent. It clearly shown that pigeonpea adopters mean consumption expenditure per adult equivalent is 72% higher. When non-adopters had adopted improved pigeonpea their consumption per adult-equivalent, would have been increased by 70%. These results imply that adoption of improved agricultural technologies increased household welfare measured in terms of crop income and consumption expenditure, however, the transitional heterogeneity effect for both crop income and consumption expenditure is positive, that is the effect is bigger for the farm household that did adopt with respect to those that did not adopt.

5. Conclusions

This paper evaluates the potential impact of adoption of improved chickpea and pigeonpea technologies on rural household welfare measured by crop income and consumption expenditure in rural Ethiopia and Tanzania. The study utilizes cross-sectional farm household level data collected in 2007 from a randomly selected sample of 1313 households (700 in Ethiopia and 613 in Tanzania). We estimate the casual impact of technology adoption by utilizing endogenous switching regression and propensity score matching methods to assess results robustness. This helps us estimate the true welfare effect of technology adoption by controlling for the role of selection problem on production and adoption decisions.

The causal impact estimation from both the propensity score matching and switching regression suggests the improve pigeonpea adopters have significantly higher crop income than non-adopters even after controlling for all confounding factors. The results from switching regression also confirms that adoption pigeonpea has significant impact on consumption expenditure per adult equivalent although the result from propensity score matching is not significant suggesting that controlling unobserved heterogeneities are important. for Ethiopia, propensity score matching estimates show that adoption of improved chickpea has a positive and significant effect on crop income per adult equivalent although the impact on consumption expenditure is mixed. The results from this paper generally confirms the potential direct role of agricultural technology adoption on improving rural household welfare, as higher incomes from improved technology translate into lower income poverty.

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Table 1. Conditional expectations, treatment and heterogeneity effects

Sub-samples	Decisions stage		Treatment Effects
	To adopt	Not to adopt	
Farm households that adopted	$(a)\ E(Y_{1i}/G_i=1)$	$(c)\ E(Y_{2i}/G_i=1)$	TT
Farm households that did not adopt	$(d)\ E(Y_{1i}/G_i=0)$	$(b)\ E(Y_{2i}/G_i=0)$	TU
Heterogeneity effects	BH_1	BH_2	TH

Notes: (a) and (b) represent observed expected crop income and consumption expenditures; (c) and (d) represent counterfactual expected crop income and consumption expenditures.

A_i = 1 if farm households adopted improved agricultural technologies: A_i = 0 if farm households did not adopt:

Y_{1i} = crop income and consumption expenditure if the farm households adopted

Y_{2i} = crop income and consumption expenditure if the farm households did not adopt

TT = the effect of the treatment (i.e. improved technologies) on the treated (i.e., farm households that adopted);

TU = the effect of the treatment (i.e. improved technologies) on the untreated (i.e., farm households that did not adopt);

BH = the effect of base heterogeneity for farm households that adopted (i = 1), and did not adopt (i = 2);

TH = (TT-TU), i.e., transitional heterogeneity

Table 2. Descriptive summary of variables used in estimations

Variables	Ethiopia Adopters (N =222)	Ethiopia Non-adopters (N = 478)	Ethiopia t-stat (chi-square)	Tanzania Adopters (N =202)	Tanzania Non-adopters (N = 411)	Tanzania t-stat (chi-square)
Dependent variables						
Crop income per adult equivalent (‘000 Birr/TSh)	3.29	2.87	1.65*	0.26	0.22	0.91
Consumption expenditure per adult equivalent (‘000 Birr/TSh)	3.18	2.74	3.41***	0.21	0.19	0.81
Household characteristics variables						
Age of the household head (years)	47.6	46.7	0.9	46.2	47.0	-0.73
Gender of household head (male = 1)	0.95	0.92	1.1	0.90	0.88	0.55
Household head education (years)	2.4	1.6	2.61***	6.40	5.60	2.72**
Active family labour force (adult equivalent -AE)	3.7	3.4	2.6***	3.60	3.40	1.58
Dependency ratio	1.16	1.09	1.22	0.41	0.42	-0.80
Household wealth variables and farm characteristics						
Oxen per AE (number/’000Tsh)	0.55	0.45	3.87***	12.3	10.0	1.68*
Value of farm asset owned per AE (’000 Birr/Tsh)	0.26	0.16	2.52**	72.6	88.3	0.60
Farm size per AE (ha)	0.42	0.34	3.39***	0.32	0.34	0.55
Access to off-farm activities (yes = 1)	0.35	0.40	1.49	0.85	0.77	5.39**
Farming main occupation (yes = 1)	0.94	0.94	0.10	0.93	0.94	0.61
Practice soil and water conservation (yes = 1)	0.40	0.40	0.00	0.36	0.46	6.48**
Institutional and access related variables						
Contact with government extension agents (number)	28.5	18.4	4.2***	24.75	13.99	2.91**
Own radio or TV or mobile phone (yes = 1)	0.84	0.75	7.36***	0.89	0.80	7.53***
Access to credit (1=yes)	0.87	0.81	3.93**	0.08	0.04	4.73**
Member of farmer association (yes = 1)	0.27	0.22	1.6	0.24	0.16	5.97**
Household head hold official position (yes = 1)	0.34	0.25	6.89***	0.17	0.11	3.44**
Walking distance to main market (km)	12.8	9.3	2.8***	7.20	7.40	0.49
Distance to extension service (km)	2.5	2.5	-0.08	11.6	12.00	-0.55
Experience of growing chickpea/pigeonpea (years)	22.6	19.3	3.3***	14.7	14.15	0.57
Farmers perception of improved varieties (ranked above average = 1)	0.83	0.29	179.5***	2.94	2.69	2.75***
Own donkey for transport (yes = 1)	0.89	0.82	5.31**	-	-	-
Own a cart for transport (yes=1)	-	-	-	0.24	0.13	11.37***
Own bicycle (yes =1)	0.01	0.02	1.27	0.66	0.58	3.15*

Note: Statistical significance at the 99% (***), 95% (**) and 90% (*) confidence levels. T-test and chi-square are used for continuous and categorical variables, respectively.

Table 3. Impact of agricultural technology adoption on income and consumption expenditure using PSM methods

Countries	Adopters	Non-adopters	Difference = average treatment effect on the treated (ATT)	t-stat
(a) Dependent variable: Log crop income per adult equivalent unit				
Method 1: Nearest neighbour matching				
Tanzania	11.59	10.61	0.98	1.68*
Ethiopia	3.35	3.07	0.29	1.74*
Method 2: Kernel matching				
Tanzania	11.59	10.88	0.71	1.61*
Ethiopia	3.28	3.17	0.11	0.79
(b) Dependent variable: Log consumption expenditure per adult equivalent unit				
Method 1: Nearest neighbour matching				
Tanzania	5.16	5.134	0.03	0.24
Ethiopia	3.41	3.38	0.04	0.87
Method 2: Kernel matching				
Tanzania	5.18	5.16	0.01	0.12
Ethiopia	3.42	3.35	0.07	1.61*

Note: Statistical significance at the 99% (***), 95% (**) and 90% (*) confidence levels. The number in brackets shows bootstrapped standard errors with 100 replication samples.

Table 4a. Full information maximum likelihood estimates of the switching regression model

Dependent variable: pigeonpea adoption and log consumption expenditure per adult equivalent for Tanzania

Variables	FIML Endogenous Switching Regression		
	Adoption (1/0)	Adoption =1 (adopters)	Adoption=0 (non-adopters)
Age of household head	0.001(0.00)	0.001(0.00)	0.001 (0.00)***
Head education 1-4 years	0.126 (0.25)	-0.651 (0.20)***	-0.043 (0.13)
Head education 5-8 years	0.375 (0.24)	-0.578 (0.19)***	-0.187 (0.13)
Head education 9-12 years	0.284(0.35)	-0.634 (0.25)**	-0.144 (0.21)
Head education >12 years	-0.234 (0.59)	0.000 (0.48)	0.492 (0.34)
Family size in AE	0.018 (0.03)	-0.077 (0.02)***	-0.089 (0.01)***
Gender of household head	-0.158 (0.20)	-0.240 (0.15)*	-0.055 (0.11)
Land per AE	0.088 (0.16)	-0.020 (0.05)	0.109 (0.04)***
Log non-oxen asset per AE	-0.088 (0.07)	0.108 (0.04)***	0.093 (0.03)***
Log oxen per AE	-0.008 (0.01)	-0.002 (0.01)	-0.004 (0.01)
Log crop income per AE	0.047 (0.03)*	-0.011 (0.02)	0.015 (0.01)
Log off-farm income per AE	0.099 (0.04)**	0.042 (0.02)*	0.046 (0.02)**
Log livestock income per AE	0.05 (0.03)	-0.003 (0.02)	0.027 (0.02)
Karatu district (reference)			
Kondoa district	-1.408 (0.43)***	0.061 (0.27)	-0.179 (0.09)*
Babati district	0.571 (0.18)***	-0.073 (0.14)	-0.397 (0.10)***
Arumeru district	0.844 (0.18)***	-0.118 (0.14)	-0.032 (0.11)
Total rented in land	0.079 (0.05)		
Land per AE square	-0.019 (0.03)		
Log of distance to nearest agricultural office	-0.182 (0.06)***		
Log of distance to the main market	-0.096 (0.07)		
Log of contact with government extension agent	0.163 (0.06)***		
Log of contact with non-government extension agent	0.077 (0.05)		
Practice soil and water conservation	-0.106 (0.16)		
Member of cooperative or community group	0.199 (0.25)		
Had information related with farm technology	0.332 (0.21)		
Access to credit	0.464 (0.23)**		
Access to seed	0.807 (0.19)***		
Access to media	0.302 (0.19)		
Owned ox-cart	0.141 (0.18)		
Owned bicycle	0.233 (0.15)		
Access to off-farm	-0.416 (0.21)**		
Predicted value of maize	-1.024 (1.12)		
Constant	-0.253 (0.74)	5.394 (0.56)***	4.412 (0.33)***
σ_{ei}		0.615 (0.04)	0.717 (0.03)
φ_{j}		-0.372 (0.19)*	-0.859 (0.04)***

Notes: absolute value of robust standard error in parenthesis,
*Significant at the 10% level, ** significant at 5%, and *** significant at 1% level.

Table 4b. Full information maximum likelihood estimates of the switching regression model

Dependent variable: pigeonpea adoption and log crop income per adult equivalent for Tanzania

Variables	FIML Endogenous Switching Regression		
	Adoption (1/0)	Adoption =1 (adopters)	Adoption=0 (non-adopters)
Age of household head	0.017 (0.17)	-0.006 (0.68)	0.0 12 (0.40)
Family size in AE	-0.072 (0.07)	-0.011 (0.04)	-0.03 (0.04)
Education of household head	0.074 (0.02)***	-0.052 (0.06)	0.002 (0.04)
Log oxen per AE	0.004 (0.02)	-0.001 (0.03)	-0.018 (0.02)
Log non-oxen asset per AE	0.055 (0.11)	0.179 (0.10)*	0.114 (0.09)
Land per AE	0.025 (0.20)	0.376 (0.13)***	0.485 (0.14)***
Total area under pigeonpea	-0.046 (0.09)	0.114 (0.11)	0.147 (0.10)
Total area under maize	0.039 (0.10)	-0.173 (0.14)	-0.116 (0.11)
Log of maize marketed	0.047 (0.03)	0.120 (0.03)***	0.039 (0.04)
Average price of maize	0.001 (0.00)***	0.004 (0.00)***	0.007 (0.00)***
Average price of pigeonpea	-0.04 (0.04)	0.258 (0.08)***	0.316 (0.06)***
Farming as primary occupation	0.003 (0.38)	-0.021 (0.34)	-0.357 (0.74)
Access to market information	-0.091 (0.15)	0.768 (0.39)*	0.253 (0.26)
Access to credit	-0.112 (0.28)	-0.164 (0.34)	0.234 (0.50)
Had information related with farm technology	0.256 (0.25)	-0.248 (0.30)	-0.191 (0.34)
Access to off-farm	0.088 (0.18)	-0.10 (0.25)	-0.398 (0.27)
Access to seed	1.128 (0.22)***	0.048 (0.33)	0.607 (0.54)
Karatu district (reference)			
Kondoa district	-2.737 (1.21)**	0.053 (0.37)	-0.26 (0.23)
Babati district	0.846 (0.27)***	0.164 (0.31)	-0.726 (0.34)**
Arumeru district	1.086 (0.23)***	-0.122 (0.10)	-0.021 (0.09)
Total rented in land	0.225 (0.13)*		
Land per AE square	-0.043 (0.03)		
Log of distance to nearest agricultural office	-0.348 (0.13)***		
Log of distance to the main market	0.004 (0.09)		
Log of contact with government extension agent	0.208 (0.08)***		
Log of contact with non-government extension agent	0.133 (0.06)**		
Practice soil and water conservation	0.356 (0.40)		
Member of cooperative or community group	1.032 (0.60)*		
Age of household head square	0.00 (0.00)		
Access to media	0.52 (0.40)		
Owned ox-cart	0.546 (0.33)*		
Owned bicycle	0.494 (0.32)		
Predicted value of maize	-5.148 (3.77)		
Constant	-6.454 (9.22)	7.975 (3.30)**	7.975 (3.30)**
σ_{ei}		1.622(0.12)	2.123 (0.08)
φ_{j}		-0.158 (0.22)	-0.342 (0.26)*

Notes: absolute value of robust standard error in parenthesis,
*Significant at the 10% level, ** significant at 5%, and *** significant at 1% level.

Table 5. Average expected crop income and consumption expenditure per adult equivalent for pigeonpea adopters and non adopters in Tanzania

Sub-samples	Decisions stage		Treatment Effect
	To adopt	Not to adopt	
a) Log crop income per adult equivalent			
Farm households who adopted	(a) 11.61	(c) 10.52	1.09(6.7)***
Farm households who did not adopt	(d) 11.37	(b) 10.93	-0.44 (3.28)***
Heterogeneity effects	BH_1= 0.24	BH_2= -0.41	TH= 1.53
b) Log consumption expenditure per adult equivalent			
Farm households who adopted	(a) 5.16	(c) 4.42	0.74(14.9)***
Farm households who did not adopt	(d) 4.94	(b) 5.64	-0.70 (19.9)***
Heterogeneity effects	BH_1= 0.22	BH_2= -1.22	TH= 1.44

Note: absolute value of t-statistic in parenthesis,
*Significant at the 10% level, ** significant at 5%, and *** significant at 1% level.