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Impact of modern agricultural technologies on smallholder welfare: Evidence from Tanzania and Ethiopia

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ABSTRACT

This paper evaluates the potential impact of adoption of improved legume technologies on rural household welfare measured by consumption expenditure in rural Ethiopia and Tanzania. The study utilizes cross-sectional farm household level data collected in 2008 from a randomly selected sample of 1313 households (700 in Ethiopia and 613 in Tanzania). The causal impact of technology adoption is estimated by utilizing endogenous switching regression. 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 consumption expenditure (in per adult equivalent terms) in rural Ethiopia and Tanzania. This confirms the potential role of technology adoption in improving rural household welfare as higher consumption expenditure from improved technologies translate into lower poverty, higher food security and greater ability to withstand risk. An analysis of the determinants of adoption highlighted inadequate local supply of seed, access to information and perception about the new cultivars as key constraints for technology adoption.

Introduction

In much of sub-Saharan Africa (SSA), agriculture is a strong option for spurring growth, overcoming poverty, and enhancing food security. Of the total population of SSA in 2003, 66% lived in rural areas and more than 90% of people in these regions depended on agriculture for their livelihoods. Improving the productivity, profitability, and sustainability of smallholder farming is therefore the main pathway out of poverty (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 the area under cultivation. Agricultural research and technological improvements are therefore crucial to increasing agricultural productivity and thereby reducing poverty and meeting demands for food without irreversible degradation of the natural resource base. However, it is widely argued that research often neglected the unfavored 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 present an opportunity in reversing the rising trends of poverty and food insecurity. In part, this is because legumes have the capacity to fix atmospheric nitrogen in soils and thus improve soil fertility and save fertilizer costs in subsequent seasons. Second, it encourages 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; Asfaw et al., 2011). Often the traditional variety dominates the local and export markets; however, low productivity of the variety limits farmers' competitiveness in these markets.

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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 thrust was to identify disease-resistant types that combined 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 and these are becoming popular in Tanzania (Shiferaw et al., 2008; Amare et al., 2012).

The underlying objectives of breeding and releasing new varieties are to reduce hunger, malnutrition, poverty and increase the incomes of poor people living in drought-prone areas of SSA. Drawing from existing literature, benefits from improved agricultural technologies have influenced the poor directly by raising incomes of farm households and indirectly by raising employment, wage rates of functionally landless laborers and by lowering the price of food staples (de Janvery and Sadoulet, 2001; Irz et al., 2001). However, most of the impact studies related to modern agricultural technologies were conducted for staple crops such as maize, wheat and rice (Mendola, 2007; Otsuka, 2000; Rahman, 1999). Very few studies have looked at the impact of improved legume technologies under smallholder agriculture. Most previous research related to legume technologies has failed to move beyond estimating economic surplus and return to research investment (e.g., Alwang and Siegel, 2003; Moyo et al., 2007).

This paper aims to contribute to the literature by providing a micro perspective on the impact of legume technology using household survey data from a random cross-section sample of 1313 small-scale producers (700 in Ethiopia and 613 in Tanzania). Specifically, we try to provide rigorous empirical evidence on the role of improved chickpea and pigeonpea technology adoption on household welfare outcomes measured by consumption expenditure per adult equivalent unit (AEU) in rural Ethiopia and Tanzania. Assessing the impact of legume technology adoption can assist with setting priorities, providing feedback to 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). Nowadays there is clear demand for greater institutionalization of impact assessment and impact culture to generate a better understanding of the complexities of the links between agricultural technology and poverty.

It is however important to note that this paper looks exclusively at the partial equilibrium effects of the new pigeonpea and chickpea technology on producers' welfare. The evidence from the Green Revolution (Evenson and Gollin, 2003) and basic intuition given price inelastic demand for basic foods such as pigeonpea and chickpea suggest that the main welfare gains from agricultural technology improvements might accrue to consumers, not producers. It may be, however, that these new varieties have not diffused sufficiently to generate significant aggregate supply growth and thus there are no discernible general equilibrium price effects associated with technological change. It might also be the case that the biggest beneficiaries of agricultural technology change are farm workers who are net crop buyers, thereby enjoying both the consumer surplus benefits of lower prices and employment and/or wage effects associated with induced expansion of farmers' demand for hired labor. Although answering these questions are important to provide a more comprehensive assessment of the true welfare impact of the new agricultural technologies, the data to evaluate such effects are lacking and they are beyond the scope of this manuscript.

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 wellbeing. Technology adoption may result in productivity enhancement for small-scale producers and better welfare status, but it may also be that better welfare status leads to more technology adoption. This paper acknowledges that the differences in welfare outcome variables between adopters of improved technologies and non-adopters could be due to unobserved heterogeneity. Failure to account for this potential unobserved heterogeneity could lead to inconsistent estimates of the impact of technology adoption. We employ endogenous switching regression method to account for endogeneity of the adoption decision due to unobserved characteristics of farmers and their farm.

The rest of the paper is organized as follows. Section two provides an overview of chickpea and pigeonpea production in Ethiopia and Tanzania. The third section presents the conceptual framework and analytical methods with emphasis on empirical models and hypothesized relationships. Survey design and descriptive results are presented in section four. The main analytical results are presented and discussed in section five. Section six concludes by presenting the key findings and the policy implications.

Overview of varietal development and transfer in East Africa

Ethiopia is the largest producer of chickpea in Africa, accounting for about 46% of the continent's production during 1994–2006 (FAOSTAT). It is also the seventh largest producer worldwide and contributes about 2% to the total world chickpea production. Chickpea, locally known as *shimbra*, is one of the major pulse crops in Ethiopia (other pulse crops include faba bean, field pea, haricot bean, lentil and grass pea) and in terms of production it is the second most important legume crop after faba beans. It contributed about 16% of the total pulse production during 1999–2008 (CSA). The total annual average (1999–2008) of chickpea production is estimated at about 173 thousand tones. During the same period, chickpea was third after faba beans and field peas in terms of area coverage.

At present the use of improved chickpea production technology packages is negligible. Over the last three decades (1974–2005), 11 improved chickpea varieties (six *kabuli* and five *desi*) were released in Ethiopia. However, the adoption rate of these varieties is very low. Official estimates from the Ethiopian Institute of Agricultural Research (EIAR) show that, of the total chickpeas cultivated area, only 10–15% was covered by improved chickpea seeds in 2008. The main reasons indicated for low adoption rates are insufficient seed production and marketing systems that limit the availability of quality improved seeds, lack of credit, late delivery, and theft during the green stage (Byerlee, 2000; Shiferaw and Teklewold, 2007). Although chickpea is widely grown in Ethiopia, the major producing areas are concentrated in two states – Amhara and Oromia. These two states cover more than 90% of the entire chickpea area and constitute about 92% of the total chickpea production (CSA). The top nine chickpea producing zones (North Gonder, South Gonder, North Shewa, East Gojam, South Wello, North Wello, West Gojam, Gonder Zuria) belong to the Amhara region and account for about 80% of the country's chickpea production. In the Oromia region, the major producing zones are in West Shewa, East Shewa and North Shewa, which account for about 85% of the total area and production.

Pigeonpea is another important grain legume widely grown and adapted to the semi-arid regions of South Asia and Eastern and

Southern Africa. The largely drought-tolerant crop allows poor families to protect their livelihoods and meet their food and cash income needs when most other crops fail in areas with erratic rainfall. Farmers in land-scarce areas can intensify land use and harvest two crops through intercropping with cereals (such as maize and sorghum) allowing farmers to minimize risk and maximize incomes.

Pigeonpea is a tradable crop both in local and international markets, and export demand (mainly to south Asia) often outstrips supply (Joshi et al., 2001; Lo Monaco, 2003). Smallholder farmers market a substantial portion of the annual produce to meet their cash requirements. Tanzania is one of the major growers and exporters of the crop in the region. Tanzania exports significant amounts (30–40 thousand tones/year) to India, and there is a growing processing and value-adding industry that would allow the country to export de-hulled split pea (*dhal*) to the Far East, Europe, and America.

However, the pigeonpea industry in Tanzania has been affected by poor productivity and limited marketed surplus produce from smallholder farmers. The poor yields are mainly due to low yielding and disease susceptible local varieties. Farmers even abandoned production of this important crop mainly due to fusarium wilt, a fungal soil-borne disease that devastates the crop. Once the field is infested with the disease, the fungus can stay in the soil for a long period of time, making it very difficult for poor farmers to control it without the use of extended rotations or expensive chemicals. The disease is pervasive in all pigeonpea growing areas in eastern and southern Africa and spreads among fields through agricultural equipment and field operations (Gwata et al., 2006).

A screening program for fusarium resistance was initiated as a concerted effort between ICRISAT and Tanzanian researchers in the early 1990s. The main thrust was to identify disease-resistant types that combine market and farmer-preferred traits. By 1997, this effort resulted in the development of 21 varieties that were successfully tested on-station, which was followed by participatory on-farm testing and evaluation of a few promising lines. Two of these fusarium-resistant improved pigeonpea (FRIP) varieties (ICEAP 00040 and 00053), which embody farmer and market-preferred traits are becoming popular in northern Tanzania.

The hypothesis for our study is that this research and development effort has had significant economic benefits and, more importantly, may improve welfare of households in Tanzania and Ethiopia. Despite higher seed prices, economic benefits to producers and consumers may result from higher productivity, lower average production costs, reduced crop loss from disease, lower food prices, and increased marketable surplus. For instance our Ethiopia survey data indicates that on average there is a 21% yield increase (from 2110 to 2660 kilograms per hectare) and a 13% cost reduction (from 294 to 326 US$ per hectare) from growing these improved chickpea varieties, compared to traditional varieties.

Conceptual framework and estimation strategies

Adoption decision and household welfare

Smallholder farmers in Tanzania and Ethiopia are simultaneously involved in both production and consumption decisions. As in many developing countries in Africa, smallholder farmers face imperfect input and credit markets. Lack of employment opportunities in rural areas for many farm households also implies that labor markets are either missing or highly imperfect. These market failures results from poverty, underdeveloped non-farm sector, asymmetric information and high transaction costs, especially in credit and input markets. In such situations, the relevance of a separable household model where consumption and production decisions are made independently is questionable. The non-separable household model provides a suitable framework for analyzing household micro-economic behavior under market imperfections. This implies that household resource allocation including on-farm technology adoption and off-farm labor supply is determined simultaneously rather than recursively (de Janvry et al., 1991).

Households in Ethiopia and Tanzania like any other society are also endowed with natural, human, financial, physical and social capital resources which constitute the resource constraint based on which they maximize their well-being. These resources are affected by exogenous factors such as agro-climatic conditions, insect pests and diseases which hinder their productivity. Change in technology used through the development of improved varieties which have better characteristics (drought tolerance, high yield, etc.) and their dissemination through different mechanism affect the farmers' perception, expectations and preference toward different varieties and inputs used in production. These in turn will condition their decisions in term of investment, crops and varietals choice, and resource allocation to various inputs. Expectedly, this would affect their consumption, marketing of harvested quantities of different crop varieties, savings, and income generation activities. In short, adoption of improved chickpea/pigeonpea varieties may not only affect the chickpea/pigeonpea sector, but it may also induce changes in cropping patterns and allocation of farmers' own resources to different use. Such changes may also contribute to expenditure changes. Therefore, household decisions and choice constitute their behavioral outcomes which will finally affect their consumption expenditure (welfare outcomes).

A simple mode of adoption and its resulting effect on outcomes can illustrate this concept more clearly. Foster and Rosenzweig (2003) and de Janvery et al. (2010) point out that the adoption and input uses are the outcomes of optimizing by heterogeneous agents. The optimization takes place in the presence of constraints on the budget, information, credit access and the availability of both the technology and other inputs. Thus, households are assumed to maximize their utility function subject to these constraints. Viewing adoption through the lens of optimization by rational agents, households adopt a given technology if only if adoption is actually a choice that can be taken and at the same time adoption is expected to be profitable or otherwise advantageous (de Janvery et al., 2010). Following de Janvery et al. (2010), Becerril and Abdulai (2010), Ali and Abdulai (2010), the adoption decision can be modeled in a random utility framework. The difference between the utility from adoption (U_{Ai}) and non-adoption (U_{Ni}) of improved chickpea/pigeonpea varieties may be denoted as G^*, such that a utility-maximizing farm household, *i*, will choose to adopt an improved variety, if the utility gained from adopting is greater than the utility of not adopting ($G^* = U_{Ai} - U_{Ni} > 0$). Since these utilities are unobservable, they can be expressed as a function of observable elements in the following latent variable model:

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

where *G* is a binary indicator variable that equals 1 if a farmer plant an improved variety and zero otherwise; β is a vector of parameters to be estimated; *X* is a vector of explanatory variables; and *u* is the error term.

In situations where input and output markets are missing or imperfect, the level of poverty/wealth affects production activities of the households. Per adult equivalent unit (AEU) non-oxen asset, per AEU oxen and per AEU farm size as wealth indicator variables were included in the adoption equation. These variables provide production services and are resources available to the farmer in his farming activity and we expect these variables to increase the likelihood of adoption for a given household. Human capital variables and/or household-specific characteristics such as family labor force, education level of household head, age and gender of the household head were also included in the adoption model. Labor availability is expected to positively affect the adoption decision. It is also expected that education will have a positive effect on the adoption decision. The exact effect of age on the adoption decision is ambiguous a priori. Younger farmers may be more innovative and have lower risk aversion behavior but they also have less farming experience. Thus, the ultimate effect is an empirical question.

Information and awareness related variables such as number of improved varieties known during previous year, history of participation in participatory variety selection (PVS), contact with government and non-government extension agents and distance to nearest agricultural office were included as explanatory variables in the model. The lagged variable for number of improved varieties known to avoid potential endogeneity problem was used. It is expected that these variables will be correlated with the farmers' awareness about the advantages of the new varieties and hence positively affect the adoption decision. A variable capturing perception of farmers about technology characteristics based on agronomic (grain yield, drought, disease tolerance, etc.) and market attributes (grain color, grain size and price)[1] was also included. Variables capturing access such as credit, seed, media, ownership of transport equipment, group membership and off-farm are also included. It is however worth noting that some important variables such as group membership and participation in off-farm activities are excluded from the right-hand side of the model since they are arguably endogenous to the technology adoption decision. Specific context and location variables such as distance from main market and district dummies were also included in the model. Distance from main market can proxy the 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 differences in infrastructure, remoteness, rainfall, resource endowment and farming conditions across regions.

Considering that the variable of interest here – consumption expenditure per AEU – is a linear function of observed variables along with a dummy variable for improved chickpea/pigeonpea variety use, the linear regression equation can be specified as

$$Y_i = \alpha J_i + \eta G_i + e_i \tag{2}$$

where Y_i represent outcome variables, G_i is an indicator variable for adoption as defined above, J_i are observable variables, α and η are vectors of parameters to be estimated, and is a error term. The impact of adoption on the outcome variable is measured by the estimates of the parameter η. This approach, however, might generate biased estimates because it assumes that the adoption of improved technology is exogenously determined while it is potentially endogenous. The decision to adopt or not is not voluntary and may be based on individual self-selection. Farmers who adopted may have systematically different characteristics from the farmers who did not adopt, and they may have decided to adopt based on expected benefits. Unobservable characteristics of farmers and their farms 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. The solution is to explicitly account for such endogeneity using simultaneous equation models (Hausman, 1978). In experimental studies, this problem is addressed by randomly assigning improved seeds to treatment and control households, which assure that using improved seeds is the only differentiating factor between treated households and those excluded from it, so that the control group can be used to assess what would have happened to adopters in the absence of the intervention (de Janvery et al., 2010). The main advantage of random assignment is that it guarantees that the treatment status is uncorrelated with any other variables, both observable and unobservable, and as a result the potential outcomes will be statistically independent of the treatment status. That means that with random assignment, all the characteristics of the households are equally distributed between treated and untreated groups. However, improved technology in our case 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 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 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 should it be assumed to raise the productivity of factors of production by way of slope shifts in the expenditure 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 the use of an endogenous switching regression model that accounts for both endogeneity and sample selection (Freeman et al., 2001; Alene and Manyong, 2007; Di Falco et al., 2011).

Endogenous switching regression model

Consider the following model, which describes the welfare outcome of households with two regression equations, and a criterion function G_i that determines which regime the household faces

$$G_i^* = \beta X_i + u_i \tag{3}$$

$$\text{Regime 1}: Y_{1i} = \alpha_1 J_{1i} + e_{1i} \quad \text{if } G_i = 1 \tag{4a}$$

$$\text{Regime 2}: Y_{2i} = \alpha_2 J_{2i} + e_{2i} \quad \text{if } G_i = 0 \tag{4b}$$

where G_i^* is the unobservable or latent variable for technology adoption, G_i is its observable counterpart, X_i are non-stochastic vectors of observed farm and non-farm characteristics determining adoption, Y_i is household consumption expenditure per AEU in regimes 1 (adopters) and 2 (non-adopters), J_i represents a vector of exogenous variables thought to influence consumption expenditure and u_i & e_i are random disturbances associated with the adoption of improved technology and welfare outcome variable, respectively. The consumption expenditure function includes covariates such as household characteristics (e.g., age, gender, family size, education),

[1] We asked farmers to score their preferred traits improved varieties (using local varieties as a reference) for each of the agronomic and market related traits. The scores are coded from very poor (coded as 1) to very good/excellent (coded as 5), which suggest the direct relationship between the score and the importance of the variety in terms of specific traits. The variable included here captures the overall score for the improved varieties across the different characteristics – the higher the score the higher the farmers' preference for the improved varieties compared to local varieties.

assets (e.g., oxen and non-oxen asset, land), cash income (crop, off-farm, livestock) from previous year, improved crop variety adoption other than chickpea/pigeonpea, district dummies, etc.

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

$$\operatorname{cov}(e_{1i}, e_{2i}, u_i) = \begin{pmatrix} \sigma_{e1}^2 & \cdot & \sigma_{e1u} \\ \cdot & \sigma_{e2}^2 & \sigma_{e2u} \\ \cdot & \cdot & \sigma_u^2 \end{pmatrix} \quad (5)$$

where σ_u^2 is the variance of the error term in the selection equation (3), (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 (4a) and (4b), 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 (3) u_i is correlated with the error terms of the welfare outcome functions (4a) and (4b) (e_{1i} and e_{2i}), the expected values of e_{1i} and e_{2i} conditional on the sample selection are non-zero:

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

where $\phi(.)$ is the standard normal probability density function, $\Phi(.)$ 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 covariance σ_{e1u} and σ_{e2u} are statistically significant, then the decision to adopt and the welfare outcome variable 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; Di Falco et al., 2011). The FIML method simultaneously estimates the probit criterion or selection equation 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 (3) and (4a and b) can be given as:

$$LnL_i = \sum_{i=1}^{N} G_i\left[\ln\phi\left\langle\frac{e_{1i}}{\sigma_{e1}}\right\rangle - \ln\sigma_{e1} + \ln\Phi(\varphi_{1i})\right] + (1-G_i)\left[\ln\phi\left\langle\frac{e_{2i}}{\sigma_{e2}}\right\rangle - \ln\sigma_{e2} + \ln(1-\Phi(\varphi_{2i}))\right] \quad (6)$$

where $\varphi_{ji} = \frac{(\beta X_i + \gamma_j e_{ji}/\sigma_j)}{\sqrt{1-\gamma_j^2}}$, $j_i = 1, 2$, with γ_j denoting the correlation coefficient between the error term u_i of the selection equation (3) and the error term e_{ij} of equation (4a) and (4b), 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, the usual order condition that X_i contains at least one element not in J_i was followed, imposing an exclusion restriction on equation (6). Our hypothesis is that the probability of a household to adopt improved technology is an increasing function of its prior exposure reflected by three selection instruments: access to information from GO extension workers, access to information from NGO extension workers and experience in participatory variety selection (PVS) during the last year. Following Di Falco et al. (2011), we establish the acceptability of these instruments by conducting a simple rejection test: if a variable is a suitable selection instrument, it will affect the technology adoption decision but it will not affect the welfare outcome variable among households that did not adopt improved varieties. Results show that all the three variables can be considered as suitable selection instruments for the case of pigeonpea in Tanzania whereas we used only two selection instruments for the case of chickpea in Ethiopia.

Conditional expectations, treatment and heterogeneity effects

Following Di Falco et al. (2011), the aforementioned endogenous switching regression model can be used to compare the expected consumption expenditure of adopters of improved technologies (a) with respect to the non-adopters (b), and to examine the expected consumption expenditure in the counterfactual hypothetical cases that the adopters did not adopt (c), and that the non-adopters adopted (d). The conditional expectations for our outcome variable in the four cases are presented in Table 1 and defined as follows:

$$E(Y_{1i}/G_i = 1) = \alpha_1 J_{1i} + \sigma_{e1u}\lambda_{1i} \quad (7a)$$

$$E(Y_{2i}/G_i = 0) = \alpha_2 J_{2i} + \sigma_{e2u}\lambda_{2i} \quad (7b)$$

$$E(Y_{2i}/G_i = 1) = \alpha_2 J_{2i} + \sigma_{e2u}\lambda_{1i} \quad (7c)$$

$$E(Y_{1i}/G_i = 0) = \alpha_1 J_{1i} + \sigma_{e1u}\lambda_{2i} \quad (7d)$$

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) and Di Falco et al. (2011), the effect of the treatment 'to adopt' on the treated (TT) was calculated as the difference between (a) and (c)

$$E(Y_{1i}/G_i = 1) - E(Y_{2i}/G_i = 1) = J_{1i}(\alpha_1 - \alpha_2) + \lambda_{1i}(\sigma_{e1u} - \sigma_{e2u}) = TT \quad (8)$$

which represents the effect of improved agricultural technology on consumption expenditure of adopters of improved technologies. Similarly, the effect of the treatment of the untreated (TU) for non-adopter households was calculated as the deference between (d) and (b):

$$E(Y_{1i}/G_i = 0) - E(Y_{2i}/G_i = 0) = J_{2i}(\alpha_1 - \alpha_2) + \lambda_{2i}(\sigma_{e1u} - \sigma_{e2u}) = TU \quad (9)$$

We can use the expected outcomes described in (7a–d) to calculate the heterogeneity effects. Adapting Carter and Milon (2005) and Di Falco et al. (2011) to this case, "the effect of base heterogeneity" for the group of farm households that decided to adopt is defined as the difference between (a) and (d),

Table 1
Conditional expectations, treatment and heterogeneity effects. *Source*: Adapted from Di Falco et al. (2011).

Sub-samples	Decisions stage		Treatment Effects
	To adopt	Not to adopt	
Adopters	(a) $E(Y_{1i}/G_i = 1)$	(c) $E(Y_{2i}/G_i = 1)$	TT
Non-adopters	(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 consumption expenditures per AEU; (c) and (d) represent counterfactual expected consumption expenditures per AEU. $G_i = 1$ if households adopted improved agricultural technologies; $G_i = 0$ if households did not adopt:
Y_{1i} = consumption expenditure per AEU if households adopted.
Y_{2i} = consumption expenditure per AEU if households did not adopt.
TT = the effect of the treatment on the treated.
TU = the effect of the treatment on the untreated.
BH = the effect of base heterogeneity for adopters ($i = 1$), and non-adopters ($i = 2$).
TH = (TT − TU), i.e., transitional heterogeneity.

$$E(Y_{1i}/G_i = 1) - E(Y_{1i}/G_i = 0) = \alpha_1(J_{1i} - J_{2i}) + \sigma_{e1u}(\lambda_{1i} - \lambda_{2i}) = BH_1 \quad (10)$$

Similarly, for the group of non-adopters, "the effect of base heterogeneity" is the difference between (c) and (b)

$$E(Y_{2i}/G_i = 1) - E(Y_{2i}/G_i = 0) = \alpha_2(J_{1i} - J_{2i}) + \sigma_{e2u}(\lambda_{1i} - \lambda_{2i}) = BH_2 \quad (11)$$

Finally, we explore the "transitional heterogeneity" (TH), that is if the effect of adopting improved agricultural technology is larger or smaller for households that actually adopted the technologies or for non-adopters in the counterfactual case that they did adopt, that is the difference between equations (8) and (9) (i.e., (TT) and (TU)).

Data and descriptive analysis

The data used for this paper originates from a survey conducted by ICRISAT, 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*[2] and farm households in Ethiopia. In the first stage, three districts namely Minjar-Shenkora, Gimbichu and Lume-Ejere were purposively selected based on the intensity of chickpea production, agro-ecology and accessibility. These districts represent major legume producing area, highly productive, suitable agro ecology for chickpea production and 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 km 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* that grew 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. A total of 700 farm households in three districts were surveyed using the standardized survey instrument.

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 based on the intensity of pigeonpea production, agro-ecology and accessibility. Alike the Ethiopia case, the districts selected here also represent major legume producing area, highly productive, suitable agro ecology for pigeonpea production and represent one of the major pigeonpea growing areas in the country where improved varieties are beginning to be adopted by farmers. In each of the four districts three major divisions were randomly selected giving rise to a total of 12 divisions. Subsequently, two wards were randomly sampled in each of the selected divisions resulting in a total of 24 wards. Random samples of 24–27 farmers were selected from a list of farming families in each village and ward depending on population size. A total of 613 farm households in four districts were surveyed using the standardized survey instrument. The number of sampled households and their adoption status by districts are reported in Table 2.

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

In this paper, adopters are classified as farmers who planted any of the improved pigeonpea/chickpea varieties irrespective of the area planted, and non-adopters are those who did not cultivate any of the improved varieties. Many adopters did not fully allocate their land to improved varieties as they also grow traditional varieties. There is a significant amount of literature on partial and stepwise adoption of agricultural technologies which is often prompted by the need for exploiting local differences in agro-ecology and soil quality to learning and adaptation of the technology before further expansion. In the case of legumes, when full adoption is profitable, many farmers are able to save their own seed (unlike hybrids for maize and other cereals that require seed to be bought every season) and expand adoption overtime. This also allows them overcome initial seed access or liquidity constraints to buy new seeds. However, our main interest in this paper is to see whether adoption of improved varieties had any significant effect on household welfare. Therefore the adoption decision is modeled as binary variable at the household level like other previous crop variety impact studies (e.g., Kijima et al., 2008; Mendola, 2007; Berceril and Abdulai, 2010; Kassie et al., 2011; Shiferaw et al., 2008, etc.).[3]

As discussed earlier, the adoption of improved technologies can help increase productivity and consumption expenditure and thus improve the welfare of farm households. Gross margin analysis of specific crops can help to estimate a more direct impact of these technologies but comparing gross margins alone do not provide the true impact of technology adoption. Unlike other studies (e.g. Mendola, 2007; Kassie et al., 2011), who used per capita income to examine the impact of HYV rice and groundnut on income and poverty status, we rely here on per AEU consumption expenditure as a measure of household welfare which is more reliable welfare indicator and less prone to measurement error than total household income. Besides, household income indicates the ability of the household to purchase its basic needs of life while per AEU expenditure reflects the effective consumption of households and therefore provides information on food security status of households. The consumption expenditure components include 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).

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

[3] We are aware that the analysis can be extended to continuous adoption choices but for this paper we stick to binary adoption decision and we leave such analysis to future research work.

Table 2
Number of sampled households surveyed and their adoption categories by districts.

Pigeonpea adoption status (Tanzania)	Districts				Total
	Kondoa	Karatu	Babati	Arumeru	
Non-adopters	148	113	80	70	411
Adopters	6	37	76	83	202
Chickpea adoption status (Ethiopia)	Gimbichu	Lume-Ejere	Minjar-Shenkora		
Non-adopters	119	138	221		478
Adopters	30	162	30		222

In Ethiopia, the contribution of crop income to total household income is about 78% whereas chickpea income contributes 37(14)% and 31(10)% to crop income (total household income) both for adopters and non-adopters, respectively. In Tanzania, crop income account for about 64% of the total household income while pigeonpea income contributes 38(14)% and 32(11)% to crop income (total household income) both for adopters and non-adopters, respectively.[4]

Summary statistics and statistical significance tests on equality of means for continuous variables and equality of proportions for binary variables for adopters and non-adopters are presented in Table 3. Some of these characteristics are the explanatory variables of the estimated models presented further on. The Ethiopian dataset contains 700 farm households and, of these, about 32% are adopters, Average age of sample household head is about 47 years and about 6% are female-headed. No significant difference is observable in the age and gender of the household head. Adopter categories do seem to significantly vary in terms of level of education, i.e., adopters have higher proportion of household heads with higher education. This suggests that education might be correlated 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 oxen per AEU, land per AEU and non-oxen farm asset per AEU. 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 to different rural institutions. The result also depicts that the adopter categories are distinguishable in terms of perception about the existing improved chickpea varieties. Adopters have more experience in chickpea farming as well as access to credit. This simple comparison of the two groups of smallholders also suggests that adopters and non-adopters differ significantly in welfare proxy of consumption expenditure per AEU.

The Tanzanian dataset contains 613 farm households and, of these, about 33% are adopters. Results show that improved pigeonpea adopter categories are distinguishable in terms of household characteristics such as household head's years 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 although oxen and farm size per AEU are not significant. Improved pigeonpea adopters are also distinct in terms of access to extension service as indicated by number of contact with government extension agents. Moreover, unlike the chickpea adopter categories in Ethiopia, the pigeonpea adopter categories in Tanzania tend to vary significantly in terms of their membership to a community or farmer group; the share of households with farmer group membership is significantly higher for pigeonpea adopters. The results also depict that the adopter categories vary significantly in terms of perception about the existing improved pigeonpea varieties.

The pigeonpea adopter groups are also significantly distinguishable in terms of access to off-farm activities, access to credit and practicing soil and water conservation. There is also a significant difference in terms of ownership of media and transport equipments such as radio, TV, mobile phones, cart and bicycle. As far as consumption expenditure per AEU is concerned, pigeonpea adopter categories are not distinguishable.

Table 4 also presents the yield or production effect of the new varieties. The source of the observed income effect of the adoption of new varieties is expected to be the result of increase in yield and reduction in costs. As shown in Table 4, the area planted to improved chickpea and pigeonpea varieties is about 0.75 and 0.72 ha respectively whereas area allocated to local varieties is about 0.21 ha for chickpea and 1.17 ha for pigeonpea. The descriptive statistics show a productivity difference in chickpea and pigeonpea yields and also difference in variable costs between adopters and non-adopters. Both improved chickpea and pigeonpea adopters have about 21% more productivity compared to the non-adopters. The same survey data also indicates that on average there is a 13% cost reduction (from 294 to 326 US$ per hectare) from growing improved chickpea varieties, compared to traditional varieties. In Tanzania the change in variable cost is not as big as that of Ethiopia (2%).

In the subsequent part of the chapter, a rigorous analytical model is estimated to verify whether these differences in mean expenditure per AEU 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 expenditure even had they not adopted.

Estimation results and discussion

Determinants of technology adoption

The maximum likelihood estimates of the probit model of adoption of improved pigeonpea varieties in Tanzania and improved chickpea varieties in Ethiopia are presented in Table 5. It provides the driving forces behind farmers' decisions to adopt agricultural technologies where the dependent variable takes the value of 1 if the farmer adopts improved chickpea/pigeonpea technology and 0 otherwise. The results show that the coefficients of most of the variables hypothesized to influence adoption have the expected

[4] The crop income component includes annual production value of major crops produced minus paid-out costs, which include costs on seeds, fertilizer, chemicals, hired labor and oxen rental and unpaid cost which include family labor, own manure and use of own oxen. In Ethiopia we included six major crops grown in the study area namely – teff, wheat, chickpea, beans, barley and lentils – in estimating the annual production value whereas in Tanzania two major crops, namely maize and pigeonpea.

Table 3
Descriptive summary of selected variables used in estimations.

Variables	Ethiopia			Tanzania		
	Adopters (N = 222)	Non-adopters (N = 478)	t-Stat (chi-square)	Adopters (N = 202)	Non-adopters (N = 411)	t-Stat (chi-square)
Outcome variable						
Consumption expenditure per AEU ('000 US$)	0.32	0.27	3.41***	0.17	0.15	0.81
Household characteristics variables						
Age of the household head (years)	47.6	46.7	0.9	46.2	47.0	−0.73
Gender of household head (male = 1)	0.95	0.92	1.1	0.90	0.88	0.55
Household head education (years)	2.4	1.6	2.61***	6.40	5.60	2.72**
Active family labor force (AEU)	3.7	3.4	2.6***	3.60	3.40	1.58
Dependency ratio	1.16	1.09	1.22	0.41	0.42	−0.80
Household wealth variables and farm characteristics						
Oxen per AEU (number/'US$)	0.55	0.45	3.87***	9.80	7.97	1.68*
Value of farm asset owned per AEU ('000 US$)	0.03	0.02	2.52**	0.06	0.07	0.60
Farm size per AEU (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
Improved crop variety adoption other than chickpea/pigeonpea (yes = 1)	0.63	0.45	4.67***	0.56	0.36	25.4***
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. The exchange rate at the time of the survey was about 1 US$ = 1255 Tsh (Tanzania) and 1 US$ = 10 Birr (Ethiopia).

Table 4
Comparative farm-level economic benefit from chickpea and pigeonpea varieties.

Variable	Chickpea in Ethiopia			Pigeonpea in Tanzania		
	Non-adopters (N = 476)	Adopters (N = 222)	Change (%)	Non-adopters (N = 411)	Adopters (N = 202)	Change (%)
Chickpea/pigeonpea area (ha)	0.21	0.75	72.00	1.17	0.72	−62.5
Yield ('000 kg/ha)	2.11	2.66	20.68	1.31	1.64	20.3
Gross value of production ('000 US$ per ha)	1.12	1.38	18.77	1.09	1.19	9.0
Variable costs ('000 US$ per ha)	0.33	0.29	−13.01	0.64	0.63	−1.65
Net-income ('000 US$ per ha)	0.80	1.09	26.76	0.45	0.57	20.7

signs although there are some important contrasts between pigeonpea and chickpea varietal adoption. Three of the determinants namely distance nearest agricultural office, perception about the varieties and access to seed are common for both pigeonpea and chickpea whereas others are typical for each crop type.

To adopt the newly introduced varieties farmers need to be aware of the available varieties. Adoption is sometimes hampered not only by the inherent characteristics of the varieties themselves but also by lack of awareness of the end users of the technologies. The number of contacts with government and non-government extension agent, distance to nearest agricultural office and distance to the main market were used as proxies for access to information. Distance to the nearest agricultural office and turns out to be significant for both chickpea and pigeonpea adoption decision. Those farmers who reside near agricultural offices probably have better access to information about the advantages of the varieties and are likely to adopt and allocate more land to them. Contact with extension agents played a positive and significant role in affecting the likelihood of adoption for both technologies whereas contact with non-government extension agent variable is significant only for pigeonpea. Agricultural extension is the system of learning and building the human capital of farmers by giving information and exposing them to farm technologies which can increase agricultural productivity and, in turn, consumption expenditure and welfare. Farmers who are frequently visited by government and non-government extension agents tend to be more progressive and experiment with improved pigeonpea seeds. This positive effect of farmer technology awareness variable is consistent with Shiferaw et al. (2008) for improved pigeonpea varieties in Tanzania, Kristjanson et al. (2005) for cowpea varieties, Kaliba et al. (2000) for maize varieties and Geberessiliese and Sanders (2006) for sorghum in Ethiopia.

The chickpea adoption decision is positively also influenced by proxies of asset holding such as farm size, oxen and non-oxen asset

Table 5
Probit model estimates of adoption of improved pigeonpea and chickpea varieties.

Variables	Adoption decision (0/1)	
	Pigeonpea in Tanzania	Chickpea in Ethiopia
Age of household head	0.013 (0.03)	−0.026 (0.03)
Age of household head square	−0.001 (0.00)	0.001 (0.00)
Education of the head	0.044 (0.02)**	0.023 (0.01)
Family size in AEU	0.0178 (0.02)	0.171 (0.04)***
Gender of household head	0.035 (0.20)	−0.087 (0.27)
Land per AEU	0.023 (0.07)	0.509 (0.30)*
Non-oxen asset per AEU	−0.057 (0.06)	0.256 (0.13)*
Oxen per AEU	0.005 (0.01)	0.413 (0.25)*
Distance to nearest agricultural office	−0.169 (0.05)***	−0.051 (0.03)*
Distance to the main market	−0.049 (0.08)	0.219 (0.17)
Contact with government extension agent	0.138 (0.05)**	0.077 (0.02)**
Contact with non-government extension agent	0.115 (0.06)*	–
Practice soil and water conservation	−0.121 (0.13)	−0.030 (013)
Number of improved varieties known	0.331 (0.25)	0.233 (0.08)***
Experience in participator variety selection (PVS) last year	0.154 (0.08)*	0.112 (0.05)**
Perception	0.193 (0.06)***	0.898 (0.14)***
Access to credit	0.259 (0.24)	0.036 (0.18)
Access to seed	0.807 (0.22)***	0.342 (0.21)**
Access to media	0.118 (020)	0.118 (0.16)
Owned ox-cart/donkey for transport	0.153 (0.18)	0.232 (0.18)
Owned bicycle	0.272 ((0.16)*	–
Karatu district (reference)		
Kondoa district	−1.283 (0.28)***	–
Babati district	0.555 (0.18)***	–
Arumeru district	0.997 (0.22)***	–
Lume-Ejere district (reference)		
Minjar-Shenkora district	–	−0.643 (0.18)***
Gimbichu district	–	−0.785 (0.16)***
Constant	−1.026 (1.00)	−1.948 (0.84)**
Number of observation	613	700
Log likelihood	−283.3007	−258.7284
Lr chi^2 (24/21)	210.49	265.09
Prob > chi^2	0.000	0.000
Pseudo R^2	0.271	0.338

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

per AEU. One possible explanation is that ownership of these assets eases the access of households to improved seed and credit. Besides, ownership of livestock in developing countries often reduces the risk of food insecurity as animals are traded for food during shocks. Similar results were found by Kristjanson et al. (2005) for cowpeas in Nigeria. The results demonstrate the critical role of asset holding in promoting improved chickpea adoption among smallholders. Surprisingly, asset holding does not seem to play a crucial role in the adoption decision of pigeonpea. Pigeonpea is generally considered to be a poor household crop and as a result different NGOs and international research centers are involved in dissemination and promotion of the crop. Similar results were also reported by Shiferaw et al. (2008) for improved pigeonpea varieties in Tanzania.

Active family labor force positively affected the adoption of improved pigeonpea and chickpea varieties although the coefficient is significant for the latter. This reflects the importance of family labor (as proxied by the number of worker family members) in cultivating the new chickpea varieties. The significant positive effect also shows how family labor is important in developing countries where moral hazard associated with hired labor is common. This makes hiring labor costly for households with small family labor force. It is also possible that new varieties may require more labor. They may require improved agronomic practices (e.g. weeding, plowing, etc.) and more labor in harvesting and threshing. In addition, new chickpea varieties are sweet and tasty at the green stage and many farmers need labor to watch the fields at night to control against thievery. Some of the green chickpea sold along the roadside is stolen from farms. The positive effect of family labor variable is also consistent with Gebremedhin et al. (2009).

Farmers' perception about the improved varieties had a significant effect on the adoption decision for improved pigeonpea and chickpea. As expected, higher preferences of producers towards selected quality traits of improved chickpea and pigeonpea varieties is positively correlated with the adoption decision. Another important variable that is positive and significant in both the pigeonpea and chickpea adoption equations is access to seed. The very limited numbers of private seed enterprises and the low attention accorded to the informal seed sector narrowed the options available to farmers for obtaining modern varieties at affordable prices at the right place and time. The private sector lacks the incentive to participate in the enhanced delivery of seeds of these crops as the size of the market is small and farmers are able to use saved and recycled seed for 3–5 years. Household head attributes indexing age and gender were not significant although education is significant for improved pigeonpea adoption.

Furthermore, adoption decision was found to vary across different agro-ecological zones. District dummies included in the models are found to be highly statistically significant for both chickpea (the point of reference is Lume-Ejere) and pigeonpea (the point of reference is Karatu district). For pigeonpea in Tanzania, the coefficients for district dummy for Arumeru, Babati and Kondoa have a negative sign and are statistically significant. These indicate that farmers in the Karatu district had a significantly higher propensity of adoption of improved pigeonpea compared to those in other districts. This shows that some districts may have been targeted more than others by research and extension. For chickpea in Ethiopia, the results show that the adoption decision for improved varieties was highest in Lume-Ejere district. Lume-Ejere is located on the main inter-state road and is also

Table 6
Full information maximum likelihood estimates of the switching regression model. Dependent variable: pigeonpea adoption and log consumption expenditure per AEU for Tanzania.

Variables	FIML endogenous switching regression	
	Adoption = 1 (adopters)	Adoption = 0 (non-adopters)
Age of household head	0.001 (0.00)	0.001 (0.00)***
Head education 1–4 years	−0.647 (0.19)***	−0.042 (0.12)
Head education 5–8 years	−0.576 (0.18)***	−0.185 (0.14)
Head education 9–12 years	−0.636 (0.24)**	−0.146 (0.21)
Head education >12 years	0.000 (0.49)	0.491 (0.34)
Family size in AEU	−0.076 (0.02)***	−0.088 (0.01)***
Gender of household head	−0.237 (0.16)*	−0.058 (0.13)
Land per AEU	−0.022 (0.06)	0.107 (0.05)***
Log non-oxen asset per AEU	0.104 (0.05)***	0.091 (0.03)***
Log oxen per AEU	−0.002 (0.01)	−0.004 (0.01)
Improved crop variety adoption other than pigeonpea	0.346 (0.11)**	0.141 (0.10)
Log crop income per AEU from previous year	−0.010 (0.03)	0.014 (0.01)
Log off-farm income per AEU from previous year	0.043 (0.03)*	0.048 (0.04)**
Log livestock income per AEU from previous year	−0.004 (0.03)	0.028 (0.03)
Karatu district (reference)		
Kondoa district	0.057 (0.29)	−0.180 (0.10)*
Babati district	−0.072 (0.15)	−0.398 (0.11)***
Arumeru district	−0.115 (0.15)	−0.031 (0.11)
Constant	5.392 (0.58)***	4.413 (0.30)***
σ_{ei}	0.614 (0.05)	0.716 (0.04)
φ_j	−0.371 (0.20)*	−0.862 (0.06)***

Note: Statistical significance at the 99% (***), 95% (**) and 90% (*) confidence levels. The number in brackets shows absolute value of robust standard error.

closer to national agricultural research centre that develop improved chickpea varieties.

Welfare effects of technology adoption

The correlation between adoption of improved farm technology and household welfare outcomes such as consumption expenditure is theoretically complex and there are further empirical pitfalls regarding the impact evaluation problem. The consumption effect of improved crop varieties is estimated based on cross-sectional data available. An endogenous switching regression model was used to address the research questions.

The full information maximum likelihood estimates of the endogenous switching regression model that can control for unobservable selection bias are reported in Table 6 for pigeonpea adoption in Tanzania.[5] The first and second column presents the consumption expenditure function (4a) and (4b) for households that did and did not adopt improved pigeonpea technology. To analyze the correlates of consumption expenditure per AEU, a broad set of explanatory variables including household demographic factors, specific individual/household head characteristics, asset holdings, district level factors, and policy related variables, were included. 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 0.

The results suggest that both observed and unobserved factors influence the decision to adopt modern agricultural technology and welfare outcome 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 difference in the consumption expenditure equation coefficient between adopters of improved pigeonpea and non-adopters illustrates the presence of heterogeneity in the sample. The consumption expenditure function of farm households that adopted improved pigeonpea is significantly different from the consumption expenditure function of the farm households that did not adopt.[6]

Table 7 present the expected household welfare outcome (i.e. consumption expenditure per AEU) under actual and counterfactual conditions for Tanzania and Ethiopia. The predicted consumption expenditure per AEU from endogenous switching regression model are used to examine the mean consumption expenditure gap between adopters and if they had not adopted. Cells (a) and (b) represent the expected consumption expenditure per AEU observed in the sample. The expected consumption expenditure per AEU by farm households that adopted is higher than the group of households that did not adopt. Based on this simple comparison, it can be misleading to attribute the different level of observed expenditure to the adoption of improved varieties.

The last column of Table 7 presents the treatment effects of adoption of pigeonpea and chickpea respectively. The result from switching regression confirms that adoption of improved pigeonpea and chickpea technologies has a positive and significant impact on log consumption expenditure per AEU. It is clearly shown that the treatment effect for improved pigeonpea and chickpea adopters mean consumption expenditure per AEU is 0.71 and 0.22, respectively. This is equivalent to 103% for pigeonpea and 24.6% for chickpea difference in the average consumption per adult equivalent. When non-adopters had adopted improved pigeonpea, their consumption expenditure per AEU would have been increased by 99.4% whereas for chickpea it is about 20.9%.[7] These

[5] The FIML 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 is also not discussed since it is not the primary objective of the paper.

[6] Similar results were also found for chickpea adopters and non-adopters in Ethiopia. The estimated coefficient of correlation between the chickpea adoption equation and the consumption expenditure function is negative and significantly different from zero. Besides, the consumption function of farm households that adopted improved chickpea is significantly different from the consumption function of the farm household that did not adopt.

[7] The treatment effect in this unit is interpreted as percentage difference. Actually, when the outcome variable is log-transformed, multiplying the ATT by 100 is an approximation, and it's near enough only for differences <0.05 (5%). The exact percent difference is given by $100(e^{ATT} - 1)$, where e is exponential e and ATT is the average treatment effect provided by the analysis of the log-transformed variable.

Table 7
Average expected consumption expenditure per AEU for chickpea and pigeonpea adopters and non-adopters.

Sub-samples	Decisions stage		Treatment effect
	To adopt	Not to adopt	
(a) Chickpea in Ethiopia			
Farm households who adopted	(a) 3.15	(c) 2.93	0.22 (2.7)**
Farm households who did not adopt	(d) 2.89	(b) 2.70	0.19 (1.8)*
Heterogeneity effects	$BH_1 = 0.26$	$BH_2 = 0.23$	TH = 0.03
(b) Pigeonpea in Tanzania			
Farm households who adopted	(a) 12.14	(c) 11.43	0.71 (14.9)***
Farm households who did not adopt	(d) 12.63	(b) 11.94	0.69 (19.9)***
Heterogeneity effects	$BH_1 = -0.49$	$BH_2 = -0.51$	TH = 0.02

Note: Statistical significance at the 99% (***), 95% (**) and 90% (*) confidence levels. The number in brackets shows absolute value of *t*-statistic.

Table 8
Differential impact of technology adoption (stratification by farm size).

Quintiles	Tanzania			Ethiopia		
	Number of observation	Pigeonpea area (ha)	Treatment effect (consumption expenditure per AEU)	Number of observation	Chickpea area (ha)	Treatment effect (consumption expenditure per AEU)
First	125	0.37	0.32 (0.48)	154	0.20	0.15 (1.52)
Second	131	0.67	1.07 (2.17)**	133	0.18	0.25 (2.41)**
Third	128	0.98	1.27 (1.93)*	133	0.30	0.20 (2.02)**
Fourth	110	1.38	0.73 (1.14)	156	0.39	0.16 (1.60)
Fifth	119	1.91	0.61 (1.02)	124	0.52	0.15 (1.43)

Note: Statistical significance at the 99% (***), 95% (**) and 90% (*) confidence levels. *t*-Statistics in parenthesis.

Table 9
Differential impact of technology adoption (stratification by educational status).

Quintiles	Tanzania		Ethiopia	
	Number of observation	Treatment effect (consumption expenditure per AEU)	Number of observation	Treatment effect (consumption expenditure per AEU)
First	172	0.96 (1.52)	196	0.12 (1.23)
Second	135	0.66 (1.48)	110	0.15 (1.42)
Third	128	1.41 (2.53)***	218	0.24 (2.2)**
Fourth	110	0.50 (0.67)	43	0.19 (1.93)**
Fifth	68	0.50 (0.79)	133	0.16 (1.34)

Note: Statistical significance at the 99% (***), 95% (**) and 90% (*) confidence levels. *t*-Statistics in parenthesis.

results imply that adoption of improved agricultural technologies increased household welfare measured in terms of consumption expenditure per adult equivalent. However, the transitional heterogeneity effect for consumption expenditure in both countries is positive; that is the effect is bigger for the farm household that did adopt with respect to one that did not adopt.

To gain further understanding of the impact of adoption on different groups of adopters, we also examined the differential impact of adoption of improved pigeonpea and chickpea by dividing households into quintiles based on farm size and education level. Results are reported in Tables 8 and 9. As observed in Table 8, the impact of adoption of improved agricultural technologies on consumption expenditure decreases with farm size in both countries. Interestingly, gain in consumption expenditure is highest in the lower farm-size quintiles (2 and 3). As shown in Table 9, the impact of adoption is highest in the middle education quintiles (3). This result is consistent with Becerril and Abdulai (2010), who found that both the positive impact on per capita expenditure and negative impact on poverty with adoption of improved maize varieties declined with land size. These results suggest that poorer farmers and more educated farmers might benefit more from pigeonpea technologies, and that providing farmers with basic education might enhance productivity.

It is however important to note that the estimated welfare impact may not be representative for broader legume producing area in Ethiopia and Tanzania. As we indicated in the sampling method section, the selected survey districts in both countries reflect one of highly major legume producing area, highly productive and suitable agro ecology for legume production. Thus the results presented in this paper represent an 'upper' bound of welfare impacts of technology adoption from the national level perspective.

Conclusions

This paper evaluates the potential impact of adoption of improved chickpea and pigeonpea technologies on household welfare measured by consumption expenditure in rural Ethiopia and Tanzania. The study utilizes cross-sectional farm household level data collected in 2008 from a randomly selected sample of 1313 households (700 in Ethiopia and 613 in Tanzania). The causal impact of technology adoption is estimated by utilizing endogenous switching regression. This helps in estimating the true welfare effect of technology adoption by controlling for the role of selection problem on production and adoption decisions.

Two main conclusions can be drawn from the results of this study on the effect of technology adoption on household welfare.

First, the group of farm households that did adopt has systematically different characteristics than the group of farm households that did not adopt. These differences represent sources of variation between the two groups that the estimation of an OLS model including a dummy variable for adopting or not cannot take into account. Second, the switching regression results suggest that adopters of improved pigeonpea in Tanzania and chickpea in Ethiopia have significantly higher per AEU expenditure than non-adopters even after controlling for all confounding factors. The results from this paper generally confirms the potential direct role of agricultural technology adoption on improving rural household welfare, as higher gain of consumption expenditure from improved technology also mean less poverty.

The question is if the welfare effects of new varieties are so great, what explains the lack of adoption by about 70% of surveyed households in both Ethiopia and Tanzania? As shown in earlier results, the sample adoption level for chickpea and pigeonpea is about 32% and 33%, respectively. The analysis of the determinants of adoption generated very interesting results. Access to local supply of seed, access to information and perception about the new cultivars are identified as key constraints for both pigeonpea and chickpea technology adoption. This implies the need for policy to strengthen and leverage government extension services and rural institutions to promote and create awareness about the existing improved chickpea technologies. The government will need to take the lead in technology promotion and dissemination at the initial stages and in creating an enabling environment for effective participation of the private sector. Awareness campaigns for improved varieties, combined with improved local availability of improved seeds at reasonable prices offer the most promising policy mix to accelerate and expand adoption.

Policy makers need to encourage and assist private seed companies and community seed producer associations by improving access to agri-business development services and empowering cooperatives and village agro-dealers. Unlike major staples such as maize, the overall size of the legume seed market is limited. The very limited numbers of private seed enterprises and the low attention accorded to the informal seed sector narrowed the options available to farmers for obtaining modern varieties at affordable prices at the right place and time. A more flexible seed system, which is sustainable (both financially and institutionally), that meets the seed needs of a diverse group of farmers and reduces the current seed supply crises is crucial to accelerate agricultural growth and commercialization. This requires lifting the entry barriers for participation of the private seed industry and encouraging the growth of the informal sector by providing adequate access to basic or foundation seed and extension advice on seed production, processing, treatment and storage. The private sector lacks the incentive to participate in the enhanced delivery of seeds of these crops as the size of the market is small and farmers are able to use saved and recycled seed for 3–5 years. Strengthening the farmer-based seed production program and revolving seed scheme by improving farmers' skills in seed multiplication can assist in increasing the supply of seed for improved varieties both within communities and to the formal seed system.

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