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Poverty Reduction Effects of Agricultural Technology Adoption: A Micro-evidence from Rural Tanzania

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ABSTRACT *This article evaluates the impact of adoption of improved pigeonpea technologies on consumption expenditure and poverty status using cross-sectional data of 613 households from rural Tanzania. Using multiple econometric techniques, we found that adopting improved pigeonpea significantly increases consumption expenditure and reduces poverty. This confirms the potential role of technology adoption in improving household welfare as higher incomes translate into lower poverty. This study supports broader investment in agriculture research to address vital development challenges. Reaching the poor with better technologies however requires policy support for improving extension efforts, access to seeds and market outlets that stimulate adoption.*

1. Introduction

In much of sub-Saharan Africa, the agricultural sector is a key fundamental for spurring growth, overcoming poverty, and enhancing food security. However in these regions agriculture is often characterised by low use of modern technology and low productivity (Kassie et al., 2011). 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 cost effective 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.

Major objectives of breeding and releasing high yielding varieties are to reduce hunger, malnutrition, poverty and increase the incomes of poor people living in marginal areas. Synthesising insights from existing literature, benefits from improved agricultural technologies

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have reduced poverty directly by raising incomes of farm households and indirectly by raising employment, wage rates of functionally landless labourers and by lowering the price of food staples (De Janvry 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 largely in Latin America and Asia (Otsuka, 2000; Rahman, 1999; David and Otsuka, 1994; Lin, 1999; de Janvry and Sadoulet, 2001; Evenson and Gollin, 2003, Foster and Rosenzweig, 2003; Hossain et al., 2006; Janaiah et al., 2006; Mendola, 2007; Becerril and Abdulai, 2010; Wu et al., 2010). In the sub-Saharan Africa context very few studies have looked at the impact of improved agricultural technologies especially high yielding varieties of food legumes under smallholder agriculture.

This article aims to contribute to the literature by providing a micro perspective on the impact of the introduction of improved legumes varieties using household survey data from a random cross-section sample of 613 households in Tanzania. Specifically, we try to provide empirical evidence on the role of improved pigeonpea technology adoption on consumption expenditure and poverty status measured by headcount index, poverty gap index and poverty severity index. To the best of our knowledge, this study is the first empirical ex-post impact assessment on the impact of pigeonpea technology adoption on household welfare and poverty in Africa. Assessing the impact of food legume technology adoption can assist with setting priorities, providing feedback to research programmes, 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. Nowadays there is clear demand for greater institutionalisation of impact assessment and impact culture to generate a better understanding of the complexities of the links between agricultural technology and poverty.

From an econometric standpoint analysing the welfare implications of agricultural technology may be affected by unobserved heterogeneity. This article acknowledges that the differences in welfare outcome variables between those households that did and did not adopt improved technologies 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 propensity score matching (PSM) and switching regression methods to account for endogeneity of the adoption decision due to unobserved characteristics of farmers and their farms.

The rest of the article is organised as follows. Section two provides an overview of pigeonpea production in Tanzania. The third section presents the context and analytical methods with emphasis on empirical models and hypothesised relationships. Survey design and data collection methods 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.

2. Production Constraints and Significance of Pigeonpea in Tanzania

In the post-independence period, governments in Tanzania were quick to recognise the political importance of ensuring a reliable and affordable supply of food to urban consumers, and implemented a range of policies to ensure that this was achieved. The focus was on national food security, which for the most part was interpreted to mean national self-sufficiency in maize, the dominant staple of the region. The policy interventions pursued to achieve this objective included the regulation of input and/or output markets, and the provision of subsidised credit, seed and fertiliser. These policies did not have a direct impact on the pigeonpea sub-sector which was not regulated. In the early 1990s Tanzania embarked upon a process of economic structural adjustment resulting in the liberalisation of input and/or output markets, the removal of subsidies, and the elimination of foreign exchange controls. The move towards market exchange rates raised domestic producer prices for export crops, which provided additional incentives for producers. The liberalisation of domestic agricultural markets and the effects of globalisation provided new opportunities that could benefit poor farmers. A more balanced approach to agriculture is now being advocated which includes the need not only to promote food crops, but also cash crops to generate income that can be used to purchase food.

Pigeonpea is an 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 when most other crops fail in areas with erratic rainfall. Farmers in land-scarce areas can intensify land use and harvest two crops through inter-cropping with cereals (like maize and sorghum) allowing farmers to diversify risks and maximise their incomes.

The area planted to pigeonpea in SSA (sub-Saharan Africa) is estimated at 499,000 hectares (ha) with a production estimate of 363,000 metric tonnes (MT); the average yield is estimated at about 730 kilograms per ha (FAOSTAT). This region accounts for 11 percentage each of the world area and production, respectively (FAOSTAT). Malawi, Kenya, Uganda, Tanzania, DRC, Burundi, and the Comoros are pigeonpea-producing countries in SSA. About 68,000 ha of land is covered with pigeonpea in Tanzania (FAOSTAT).

Pigeonpea is a tradable crop both in local and international markets, and export demand (mainly to South Asia) often outstrips supply (Shiferaw et al., 2008). 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 (30,000–40,000 tonnes/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 problems with supply linked to 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.

A screening programme 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 reduce poverty in Tanzania. 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. Our survey data indicates that on average there is a 20 per cent yield increase (from 1310 to 1640 kilograms per hectare) and a 35 per cent cost reduction (from TSh 37,190 to TSh 34,600 per hectare)[1] from growing these new varieties, compared to traditional varieties.

3. Impact Evaluation Challenges and Estimation Strategies

Estimation of the welfare gain from the adoption of agricultural technologies based on non-experimental observations is not trivial because of the need to identify the counterfactual situation had they not had adopted the improved technology. In experimental studies, this problem is addressed by randomly assigning farmers to treatment and control status, where the welfare outcome observed on the control households (non-adopters) are statistically representative of what would have occurred without adoption for treated farmers (adopters). However, farmers are not randomly distributed to the two groups (adopters and non-adopters), but rather farmers make their own adoption choices, or are systematically selected by development agencies and/or by project administrators based on their propensity to participate in technology adoption. Therefore, adopters and non-adopters may be systematically different. Thus, possible self-selection due to observed and unobserved plot and household characteristics makes it difficult to perform ex-post assessment of gains from technology adoption using observational data.

We propose using propensity score matching (PSM) and endogenous switching regression methods to address the above econometric challenges. A limitation of PSM is that unobservable variables that may affect both the outcome variables and choice of technology are not accounted for directly; it assumes selection is based on observable variables. However, the presence of unobserved characteristics in the propensity score estimation can create mismatching and biased estimators. To address this problem, we also employed endogenous switching regression that assumes selection on unobservables. The seminal explanation of the PSM method is available from Rosenbaum and Rubin (1983), and its strengths and weaknesses are elaborated, for example, by Dehejia and Wahba (2002), Heckman et al. (1998), Caliendo and Kopeinig (2008), and Smith and Todd (2005).

Following Heckman et al. (1997), let D denote a dummy variable such that $D=1$ if the household adopt improved technology and $D=0$ otherwise. Similarly, let Y_1 be the value of welfare (that is, consumption expenditure and poverty status) when the household adopt the technology and Y_0 be the same variable when the household does not adopt the technology. The observed welfare is:

$$Y = DY_1 + (1 - D)Y_0, D = 0, 1 \tag{1}$$

Denoting P as the probability of observing a household with $D=1$, the average treatment effect, τ, can be specified as:

$$\tau = P.\lfloor E(Y_1/D = 1) - E(Y_0/D = 1)\rfloor + (1 - P).\lfloor E(Y_1/D = 0) - E(Y_0/D = 0)\rfloor \tag{2}$$

Equation (2) implies that the effect of adoption for the entire sample is the weighted average of the effect of adoption on the adopters (treated) and non adopters (controls), with each weighted by its relative frequency. The main problem of causal inference stems from the fact that the unobserved counterfactuals, $E(Y_1/D=0)$ and $E(Y_0/D=1)$ cannot be estimated (Smith and Todd, 2005).

The present study addresses this problem by using the PSM method that summarises the pre-treatment characteristics of each subject into a single index variable, and then uses the propensity score to match similar individuals (Rosenbaum and Rubin, 1983). The PSM, which is the probability of assignment to treatment conditional on pre-treatment variables, is given by:

$$p(X) = \Pr[D = 1/X] = E[D/X]; p(X) = F\{h(X)\} \tag{3}$$

Where $F\{.\}$ can be normal or logistic cumulative distribution and X is a vector of observed farm and non-farm characteristics determining technology adoption.

Estimating the treatment effects based on the propensity score requires two assumptions. The primary assumption underlying matching estimators is the Conditional Independence Assumption (CIA) which assumes that the decision to adopt is random conditional on observed covariates X. A second condition is that the average treatment effect for the treated (ATT) is only defined within the region of common support. This assumption ensures that persons with the same X values have a positive probability of being both adopters and non-adopters (Heckman et al., 1997). Once the propensity score is computed, the ATT effect can then be estimated as follows:

$$\begin{aligned} ATT &= E[Y_1 - Y_0/D = 1], \\ ATT &= E[E\{Y_1 - Y_0/D = 1, p(X)\}], \\ ATT &= E[E\{Y_1/D = 1, p(X)\} - E\{(Y_0/D = 0, p(X)\}] \end{aligned} \tag{4}$$

More specifically, the ATT is the difference between two terms with the first term being the welfare indicator for the treated group which is observable and the second term being the welfare indicator for the treated group had it not been treated, representing a counterfactual situation which is unobservable and needs to be treated.

Several matching methods have been developed to match adopters with non-adopters of similar propensity scores. Asymptotically, all matching methods should yield the same results. However, in practice, there are trade-offs in terms of bias and efficiency with each method (Caliendo and Kopeinig, 2008). Here, we use nearest neighbour matching (NNM) and kernel-based matching (KBM). The basic approach is numerically to search for 'neighbours' of non-adopters that have a propensity score that is very close to the propensity score of the adopters.

Given that the analysis does not condition on all covariates, but on the propensity score, there is the need to check if the matching procedure is able to balance the distribution of the relevant variables in the control and treatment groups. The basic idea is to compare the situation before and after matching and then check if there is any remaining differences after conditioning on the propensity score (Caliendo and Kopeinig, 2008). Although several versions of balancing tests exist in the literature, the most widely used is the mean absolute standardised bias (MASB) between adopters and non-adopters suggested by Rosenbaum and Rubin (1985), in which they recommend that a standardised difference of greater than 20 per cent should be considered too large and an indicator that the matching process has failed.

Additionally, Sianesi (2004) proposed a comparison of the pseudo R^2 and p-values of the likelihood ratio test of the joint significance of all the regressors obtained from the logit analysis before and after matching the samples. After matching, there should be no systematic differences in the distribution of covariates between the two groups. As a result, the pseudo- R^2 should be lower and the joint significance of covariates should be rejected (or the p-values of the likelihood ratio should be insignificant).

Despite the fact that propensity score matching tries to compare the difference between the outcome variables of adopters and non-adopters with similar inherent characteristics, it cannot correct unobservable bias because propensity score matching only controls for observed variables (to the extent that they are perfectly measured). If there are unobserved variables that simultaneously affect the adoption decision and the outcome variables, a selection or hidden bias problem might arise, to which matching estimators are not robust (Rosenbaum, 2002). We checked the sensitivity of the estimated average adoption effects (ATT) to hidden bias, using the Rosenbaum (2002) bounds test. This test suggests how great an effect unobservables would have to have in order to reverse the findings based on matching on observables.

We also take care for the endogeneity of the adoption decision by estimating a simultaneous equations model of technology adoption and household welfare outcome with endogenous switching by full information maximum likelihood (FIML) following Maddala and Nelson (1975), Laure (2007) and Di Falco et al. (2011). Consider the following model, which describes the welfare outcome of households with two regression equations, and a criterion function D^* that determines which regime the household faces:

$$D^* = \beta X + u \text{ with } \mathrm{D} = \begin{cases} 1 & if D^* > 0 \\ 0 & otherwise \end{cases} \tag{5}$$

$$\text{Regime 1: } Y_1 = \alpha J_1 + e_1 \quad \text{if } D = 1 \tag{6a}$$

$$\text{Regime 1: } Y_2 = \alpha_2 J_2 + e_2 \quad \text{if } D = 0 \tag{6b}$$

where D^* is the unobservable or latent variable for technology adoption, D is its observable counterpart, X are non-stochastic vectors of observed farm and non-farm characteristics determining technology adoption, Y is household consumption expenditure per capita and poverty outcome indices in regimes 1 (adopters) and 2 (non-adopters), J represents a vector of exogenous variables thought to influence consumption expenditure and poverty outcome and *u&e* is random disturbances associated with the selection and welfare outcome equations, respectively.

For the model to be identified it is important to follow the usual order condition that X contains at least one element not in J imposing an exclusion restriction. The instruments are expected to affect directly the selection variable but not the outcome variables. Our identification strategy is based on variations in the access to information and improved seeds exhibited by different households. Our hypothesis is that the probability of a household adopting improved technology is an increasing function of its prior exposure and access to improved seeds, reflected by four selection instruments: access to information from extension workers, access to information from radio/television, experience in participatory variety selection (PVS) last year and constrained access to improved seeds. 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 variables among households that did not adopt improved varieties. Results show that with exception of seed access variable, the other three variables can be considered as suitable selection instruments: they are jointly statistically significant drivers of the decision to adopt improved variety but not of the per capita expenditure and poverty status of households that did not adopt the technology.

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

$$\operatorname{cov}(e_1, e_2, u) = \begin{pmatrix} \sigma_{e1}^2 & . & \sigma_{e1u} \\ . & \sigma_{e2}^2 & \sigma_{e2u} \\ . & . & \sigma_u^2 \end{pmatrix}$$

where σ_u^2 is the variance of the error term in the selection Equation (5), (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 (6a) and (6b), and σ_{e1u} and σ_{e2u} represent the covariance of u e_1 and e_2. The covariance between e_1 and e_1 is not defined, as Y_1 and Y_2 are never observed simultaneously (Maddala, 1983). An important implication of the error structure is that because the error term of the selection Equation (5) u is correlated with the error terms of the welfare outcome functions (6a) and (6b) (e_1 and e_2), the expected values of e_1 and e_2 conditional on the sample selection are non-zero:

$$E[e_1/D = 1] = \sigma_{e1u} \frac{\phi(\beta X)}{\Phi(\beta X)} \text{ and } E[e_2/D = 0] = -\sigma_{e2u} \frac{\phi(\beta X)}{1 - \Phi(\beta X)}$$
$$= \sigma_{e1u}\lambda_1, \qquad\qquad = \sigma_{e2u}\lambda_2$$

where $\phi(.)$ is the standard normal probability density function, $\Phi(.)$ the standard normal cumulative density function, and $\lambda_1 = \frac{\phi(\beta X)}{\Phi(\beta X)}$, and $\lambda_2 = -\frac{\phi(\beta X)}{1-\Phi(\beta X)}$.

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 (5) and (6a & 6b) can be given as:

$$\begin{aligned} LnL &= \sum_{i-1}^{N} D\left[\ln \phi\left\langle \frac{e_1}{\sigma_{e1}} \right\rangle - \ln \sigma_{e1} + \ln \Phi(\varphi_1)\right] \\ &+ (1-D)\left[\ln \phi\left\langle \frac{e_2}{\sigma_{e2}} \right\rangle - \ln \sigma_{e2} + \ln(1-\Phi(\varphi_2))\right] \end{aligned} \quad (7)$$

where $\varphi_{ji} = \frac{(\beta X + \gamma_j e_j/\sigma_j)}{\sqrt{1-\gamma_j^2}}$, $j_i = 1, 2$, with γ_{j} noting the correlation coefficient between the error term u of the selection Equation (5) and the error term e of Equation (6a) and (6b), respectively.[2]

Following Di Falco et al. (2011), the aforementioned endogenous switching regression model can be used to compare the expected consumption expenditure and poverty outcome of adopters (a) with respect to the non-adopters (b), and to explore the expected consumption expenditure and poverty outcome 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 variables in the four cases are defined as follows:

$$E(Y_1/D=1) = \alpha_1 J_1 + \sigma_{e1u}\lambda_1 \quad (8a)$$

$$E(Y_2/D=0) = \alpha_2 J_2 + \sigma_{e2u}\lambda_2 \quad (8b)$$

$$E(Y_2/D=1) = \alpha_2 J_2 + \sigma_{e2u}\lambda_1 \quad (8c)$$

$$E(Y_1/D=0) = \alpha_1 J_1 + \sigma_{e1u}\lambda_2 \quad (8d)$$

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)

$$E(Y_1/D=1) - E(Y_2/D=1) = J_1(\alpha_1 - \alpha_2) + \lambda_1(\sigma_{e1u} - \sigma_{e2u}) = TT \quad (9)$$

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

$$E(Y_1/D=0) = E(Y_2/D=0) = J_2(\alpha_1 - \alpha_2) + \lambda_2(\sigma_{e1u} - \sigma_{e2u}) = TU \quad (10)$$

4. Data and Descriptive Statistics

The data used for this article originates from a survey conducted by ICRISAT 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 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.

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 legume producing areas 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 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 sampled in each of the selected divisions resulting in a total of 24 wards. About 24 to 27 farmers were then randomly sampled from a list of farming families in each ward. A total of 613 farm households in four districts were surveyed using the standardised survey instrument.

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

In this study, adopters are classified as households who planted any of the improved pigeonpea varieties, and non-adopters are those who did not cultivate any of the improved pigeonpea varieties. About 89 per cent of the total sample households are pigeonpea growers. The average area planted with improved pigeonpea varieties ranges from 0.56 hectares to 0.87 hectares.

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 1. Some of these characteristics are the explanatory variables of the estimated

Table 1. Descriptive summary of selected variables used in estimations

Variables	Adopters (N = 202)		Non-adopters (N = 411)		t-stat (chi-square)
Per capita expenditure ('000 TSh)	217.95	(186.48)	199.11	(280.23)	−0.97
Ln (per capita expenditure) ('000 TSh)	12.07	(0.64)	11.84	(0.81)	−3.52
Pigeonpea production (kg)	678.34	(978.16)	432.51	(739.87)	−3.47
Area under improved pigeonpea (ha)	0.72	(1.12)	0.00	(0.00)	NA
Total family size	6.20	(2.29)	6.08	(2.21)	−0.60
Gender of the household member (1 = male)	0.91	(0.29)	0.88	(0.33)	−1.03
Distance to the nearest main market (km)	7.18	(4.71)	7.43	(6.67)	0.48
Distance to the nearest agricultural office (km)	11.56	(7.91)	12.04	(9.63)	0.57
Experience (years) of growing pigeonpea	14.69	(10.97)	14.19	(10.87)	−0.56
Household has constrained access to seed	0.83	(0.38)	0.93	(0.25)	4.02
Ownership of ox cart	0.24	(0.43)	0.13	(0.34)	−3.84
Price of pigeonpea per household (TSh)	437.93	(171.53)	386.95	(178.91)	−3.34
Total cultivated (acres)	5.40	(6.59)	5.30	(7.46)	−0.18
Membership of rural institutions	0.24	(0.43)	0.16	(0.37)	−2.43
Education of the household member (years)	6.39	(2.59)	5.53	(2.96)	−3.51
Age of the household member (years)	46.18	(12.81)	47.01	(13.77)	0.71
Total asset value ('000 Tsh)	528.00	(1897.15)	519.35	(1548.63)	−0.07
Household rented in land	0.17	(0.38)	0.14	(0.35)	−0.02
Area under maize (ha)	1.63	(1.45)	1.46	(1.44)	−1.42
Area under beans (ha)	0.50	(1.33)	0.45	(0.90)	−0.58
Main occupation (1 = farming)	0.93	(0.25)	0.95	(0.23)	0.77
Number of contacts with extension agent	0.87	(0.34)	0.74	(0.44)	−3.71
Improved crop varieties other than pigeonpea	0.57	(0.04)	0.35	(0.02)	−5.18

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

models presented further on. The dataset contains 613 farm households and, of these, about 33 per cent adopted improved pigeonpea varieties and that there are significant differences in household characteristics. Non-adopters, for example, are more likely to be constrained by lack of access to improved seed, and they have less contact with extension agents. (Although a multivariate analysis is needed, this could explain why non-adopters do not adopt the pigeonpea technologies.) On average, a higher proportion of adopters are members of rural institutions (for example, farmers' groups and networks) and they also have more years of education. There are significant differences in ownership of an ox cart which is an indicator of wealth, as well as positively associated with farm level labour productivity. Adopters are more likely to have ox carts than their non-adopting counterparts. There are also significant differences between adopters and non-adopters with respect to total amount of pigeonpea produced.

There seem to be no significant difference between the adopter categories in terms of consumption expenditure per capita but looking closely at the data the consumption variable seems to be skewed to the right. After transforming the consumption variable into the logarithm form, the test shows a significant difference between adopters and non-adopters.

Table 2 also presents the yield or production effect of the new varieties. As discussed earlier the source of the observed poverty effect of the adoption of new varieties is expected to be the result of an increase in yield and reduction in costs. As shown in Table 2, the average of the area planted to improved pigeonpea varieties is 0.72 hectares whereas area allocated to local varieties is 1.17 hectares on average. Inadequate local supply of seed and access to information about the new cultivars are key constraints why non-adopters did not adopt and also adopters allocate more land to local varieties when improved varieties are profitable. The descriptive statistics show a productivity difference in pigeonpea yields and also a difference in variable production costs between adopters and non-adopters. Improved pigeonpea adopters are about 20 per cent more productive compared to the non-adopters. Variable costs for adopters are 34.5 per cent lower than non-adopters on average, suggesting greater benefits from this source. The simple comparisons between adopters and non-adopters demonstrate that the adopters are distinguishable in terms of pigeonpea net income with a significantly higher average.

Table 3 displays marketed surplus of adopters and non-adopters and the labour demand for pigeonpea production. The marketed surplus of adopters is significantly higher than non-adopter. One of the indirect effects of technology adoption can be an increase in demand for labour. This in turn, implies higher costs to the household, but may also generate external

Table 2. Comparative farm-level economic benefit from pigeonpea production

Variable	Adopters (N = 202)	Non-adopters (N = 411)	Difference (%)
Pigeonpea area (ha)	0.72	1.17	−62.5**
Yield ('000 kg/ha)	1.64	1.31	20.3***
Gross value of production ('000 TSh per ha)	1498.10	1363.66	9.0
Variable costs ('000 TSh per ha)	787.97	800.69	−1.65
Pigeonpea net-income ('000 TSh per ha)	710.13	562.97	20.7**

Notes: Statistical significance at the 99 per cent (***) and 95 per cent (**) confidence levels.

Table 3. Marketed surplus and labour use by adoption status

Variable	Adopters (N = 202)	Non-adopters (N = 411)	Difference
Marketed surplus of pigeonpea (kg)	536	353	183***
Labour use for pigeonpea (man-days per ha)	47	33	−12.58***

Notes: Statistical significance at the 99 per cent (***) confidence levels.

Table 4. Poverty measures by adoption status (pooled sample)

Poverty measures	Adopters (N = 202)	Non-adopters (N = 411)	Difference
Head count ratio	0.480	0.625	−0.146***
Poverty gap	0.170	0.263	−0.093***
Severity gap	0.080	0.147	−0.067***

Source: Authors' computation using FGT poverty formula.
Notes: For the above calculations TSh 468 per person per day is used as poverty line (HBS, 2007). This is basic needs poverty line for Tanzania during the survey period. The food poverty line during the same year was TSh341 per person per day.
Statistical significance at the 99 per cent (***) confidence levels.

benefits in the form of employment for the rural poor (De Janvry and Sadoulet, 2001). The adoption of pigeonpea technology in Tanzania seems to generate this kind of indirect effect, shown by the significant difference in pigeonpea labour use per hectare between adopters and non-adopters (Table 3). Holding other things constant, adoption of improved pigeonpea varieties can increase labour use by 13 person days per hectare

Table 4 compares the incidence of poverty, the poverty gap, and the poverty severity of adopters and non-adopters[3] which are computed using the Foster-Greer-Thorbecke (FGT) poverty measure. Unlike other studies (e.g. Mendola, 2007; Kassie et al., 2011), who used per capita income to examine the impact of HYV rice on income and poverty status, we rely on per capita consumption expenditure as a measure of poverty. In this study, 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 organisation, education and medical expenditure) over the 12 months (2007/2008). In the survey areas, poverty is extremely high and the depth and severity of indices show a high degree of basic need shortfall below the poverty line and a high degree of inequality among the poor (Table 4). Adopters are less poor than non-adopters, where the unconditional headcount ratio of poverty is about 14.6 percentage points lower, compared to non-adopters.

The unconditional summary statistics and tests in the tables above in general suggest that agricultural technology may have a role in improving household wellbeing, but because adoption is endogenous, a simple comparison of the welfare indicators of adopters and non-adopters has no causal interpretation. That is, the above differences may not be the result of pigeonpea technology adoption, but instead may be due to other factors, such as differences in household characteristics and the endowments mentioned above. 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 welfare even had they not adopted. Therefore, we need to add careful multivariate analysis to test the impact of pigeonpea technology adoption on household welfare.

5. Results and Discussion

5.1 Estimation of Propensity Score

The logit estimates of the adoption propensity equation are presented in Table 5. The logit model has a McFadden pseudo R^2 value of 0.11 and log likelihood value of -349. The logit estimates show that several variables are statistically significantly associated with adoption of improved pigeonpea.

Farm size, occupation, and plot number are positively associated with adoption, as are years of education and membership in local farmers' organisations. 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

Table 5. Logit model estimates of adoption of improved pigeonpea varieties

Variables	Estimates	
Total family size	−0.008	(0.050)
Gender of the household member (1 = male)	0.056	(0.324)
Distance to the nearest main market (km)	0.004	(0.014)
Ln (distance to agricultural office)	−0.011	(0.082)
Experience (years) of growing pigeonpea	0.001	(0.010)
Household has constrained access to seed	−1.506***	(0.318)
Ownership of ox cart	0.572**	(0.252)
Price of pigeonpea per household (TSh)	0.002**	(0.001)
Ln (total cultivated land)	−0.097	(0.176)
Experience in participator variety selection (PVS) last year	0.272**	(0.120)
Member of farmer groups or coops in the last 2 years	0.226	(0.235)
Education of the household member (years)	0.139***	(0.042)
Age of the household member (years)	0.015*	(0.009)
Total asset value (TSh)	−0.000	(0.000)
Household rented in land (ha)	0.005	(0.268)
Occupation (1 = farming)	0.183	(0.373)
Received information from radio/tv	0.212**	(0.112)
Received information from GO extension agent	0.474***	(0.217)
Improved crop variety other than maize	0.724***	(0.189)
Constant	−2.844***	(0.864)
Pseudo R-squared	0.1243	
Model chi-square	72.604	
Number of observations	612	
Log likelihood	−353.58	

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

of the end users of the technologies. Education, contact with extension agents and membership in farmers' groups may be proxies for access to information. The first two variables are significant in explaining the variation in the adoption decision. Agricultural extension is the system of learning and building the human capital of farmers through the provision of information and demonstrations, exposing farmers to technologies which can increase agricultural productivity and, in turn, income and welfare. Farmers who are frequently visited by extension agents tend to be more progressive and more likely to experiment with improved pigeonpea seeds. This positive effect of the 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 Gebreselassie and Sanders (2006) for sorghum in Ethiopia. Similarly, educated farmers tend to have greater ability to utilise new information and analyse the importance of new technologies.

On the other hand, lack of access to seeds (availability of seeds) is negatively associated with adoption. This implies that policy interventions that make improved pigeonpea seeds available to more farmers could facilitate adoption. This finding is consistent with the findings of Audi et al. (2009) which found formal sector pigeonpea seed supply constraints affecting adoption, although access in the informal sector, particularly in rural grain markets, was found to be an increasingly important source of improved varieties for the crop. However, poor information transmission about varietal characteristics in the informal sector is a major barrier to accessing improved varieties from this channel. In addition, the very limited numbers of private seed enterprises restricts 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 three to five years.

As expected, prices of pigeonpea have a positive influence on the adoption decision.[4] Ownership of ox carts also has a positive and significant effect on the adoption decision. Total cultivated land is negatively correlated with the adoption of improved pigeonpea but not significant. Other proxies related to asset holding do not seem to play a crucial role in the adoption decision of pigeonpea. Pigeonpea is generally considered to be a poor household's crop and as a result different non-governmental organisations (NGOs) and international research centres are involved in dissemination and promotion of the crop, targeting small and low income households Age of household head is positive and significant perhaps suggesting the role of experience in adoption. Household head attributes indexing gender and household size are not significant in explaining the adoption decision. These results are in line with the summary statistics and tests presented in Table 1.

Before turning to the causal effects of pigeonpea technology adoption, we briefly discuss the quality of the matching process. After estimating the propensity scores for the adopters and non-adopter group we check the common support condition.[5] A visual inspection of the density distributions of the estimated propensity scores for the two groups (Online Appendix, Figure 1) indicates that the common support condition is satisfied: there is substantial overlap in the distribution of the propensity scores of both adopters and non-adopters groups. The bottom half of the graph shows the propensity scores distribution for the non-adopters and the upper half refers to the adopters. The densities of the scores are on the y-axis.

As noted above, a major objective of the propensity score estimation is to balance the distribution of relevant variables between the adopters and non-adopters, rather than obtain a precise prediction of the selection treated.[6] See Online Appendix, Table 2 for detailed results of covariate balancing tests before and after matching. The standardised mean difference for overall covariates used in the propensity score (around 16% before matching) is reduced to about 5 per cent after matching. This substantially reduces total bias, in the range of 64–74 per cent through matching. The p-values of the likelihood ratio tests indicate that the joint significance of covariates was always rejected after matching, whereas it was never rejected before matching. The pseudo R^2 also dropped significantly from 11 per cent before matching to about 0.7–1.7 per cent after matching. The low pseudo R^2, low mean standardised bias, high total bias reduction, and the insignificant p-values of the likelihood ratio test after matching (see Online Appendix, Table 2) suggest that the proposed specification of the propensity score is fairly successful in terms of balancing the distribution of covariates between the two groups.

5.2 Estimation of Average Adoption Effect

Table 6 reports the estimates of the average adoption effects estimated by NNM and KBM methods. As a sensitivity analysis, the table reports estimates based on the single and five nearest neighbours, and the Epanechnikov kernel estimator with two different bandwidths. All the analyses were based on implementation of common support and caliper, so that the distributions of adopters and non-adopters were located in the same domain. As suggested by Rosenbaum and Rubin (1985), we used a caliper size of one-quarter of the standard deviation of the propensity scores. Bootstrap standard errors based on 100 replications are reported.

Four outcome variables are used in the analysis: natural logarithm of per capita consumption expenditure (hereafter consumption expenditure), headcount index, poverty gap index and severity index. The consumption expenditure is transformed into logarithmic because it is very right-skewed. The results indicate that adoption of improved pigeonpea varieties has a positive and significant effect on consumption expenditure and negative impact on poverty.

The increase in consumption expenditure ranges from 18 to 28 percentage points per capita using both algorithms. This is the average difference in consumption expenditure of similar pairs of households that belong to different technological status (that is, adopters and non-adopters). The increase in consumption expenditure can help adopters reduce their poverty level. Depending on the specific matching algorithm used, the estimated impact of technology adoption on poverty reduction as measured by head count index is estimated to range 12–13 percentage points (see Table 6).

Adoption has also had an impact on reducing the depth and severity of poverty. The estimated effect of adoption on reducing the depth of poverty in the range of 8–10 percentage points using the nearest neighbour and kernel based matching estimators (Table 6). Similarly, the adoption of improved pigeonpea varieties significantly decreases inequality (severity) of poverty in the range of 4.4–8.1 percentage points using both the nearest neighbour and kernel based matching estimators (Table 6).

Also presented in Table 6 is the result of the Rosenbaum bounds sensitivity analysis on hidden bias. The critical value of gamma (at which point we would question our conclusion of a positive effect of technology adoption on consumption expenditure and a negative effect on poverty status) starts in the range of $\Gamma = 1.55 - 1.80$. This implies that if individuals with the same covariates differ in their odds of adoption by a factor of 55–80 per cent, the significant of the technology adoption effect on outcome variables may be questionable. These are large values because we included the most important variables that affect both the adoption decision and the outcome variable. However, it is important to assess the impact of adoption using an alternative model which includes unobservable influence.

Table 7 reports the result of the impact of pigeonpea adoption on per capita expenditure and poverty using endogenous switching regression methods.[7] It presents the expected household welfare outcome (that is per capita expenditure and poverty indices) under actual and counterfactual conditions. The predicted consumption expenditure per capita and poverty indices from endogenous switching regression model are used to examine the mean consumption expenditure and poverty gap between adopters and if they had not adopted. Cells (a) and (b) represent the expected welfare outcome observed in the sample while cell (c) and (d) represent the

Table 6. Impact of pigeonpea adoption on per capita expenditure and poverty status – PSM results

	Outcome variables	Outcome mean		ATT	Critical level of hidden bias (Γ)
		Adopters	Non-adopters		
NNM[a]	ln(per capita expenditure)	12.0774	11.8301	0.24723 (2.142)***	1.60
	Head count ratio	0.4745	0.6020	−0.1276 (1.76)*	1.75
	Depth of poverty	0.1693	0.2742	−0.1049 (2.894)***	1.55
	Severity of poverty	0.0800	0.1612	−0.0812 (3.094)***	1.85
NNM[b]	Ln(Per capita expenditure)	12.0774	11.9136	0.1638 (1.70)*	1.75
	Head count ratio	0.4745	0.6087	−0.1342 (2.396)*	1.70
	Depth of poverty	0.1693	0.23727	−0.0679 (2.102)***	1.60
	Severity of poverty	0.0800	0.1242	−0.0442 (1.910)*	1.65
KBM[c]	Ln(Per capita expenditure)	12.0748	11.9091	0.1657 (1.98)*	1.65
	Head count ratio	0.480	0.602	−0.122 (2.405)	1.70
	Depth of poverty	0.170	0.254	−0.084 (2.89)***	1.80
	Severity of poverty	0.080	0.138	−0.058 (2.75)***	1.55
KBM[d]	Ln(Per capita expenditure)	12.0851	11.9024	0.1827 (2.182)***	1.80
	Head count ratio	0.4691	0.6010	−0.1319 (2.637)***	1.75
	Depth of poverty	0.1663	0.2486	−0.0823 (2.982)***	1.65
	Severity of poverty	0.0781	0.1337	−0.0556 (2.820)***	1.80

Notes: Statistical significance at the 99 per cent (***), 95 per cent (**) and 90 per cent (*) confidence levels. T-statistics in parenthesis.
The number of observations on common support for adopters and non-adopters are 194 and 410, respectively.
[a]NNM = single nearest neighbour matching with replacement, common support, and caliper (0.04).
[b]NNM = five nearest neighbours matching with replacement, common support, and caliper (0.04).
[c]KBM = kernel based matching with band width 0.06, common support, and caliper (0.04).
[d]KBM = kernel based matching with band width 0.03, common support, and caliper (0.04).

Table 7. Average expected per capita expenditure and poverty outcome – treatment effects

	Decisions stage		
Sub-samples/Outcome variables	To adopt	Not to adopt	Treatment effects
(i) Ln(Per capita expenditure)			
Adopters	(a) 12.07	(c) 11.76	TT = 0.31 (3.91)***
Non-adopters	(d) 12.14	(b) 11.85	TU = 0.29 (2.98)***
(ii) Head count ratio			
Adopters	(a) 0.48	(c) 0.61	TT = −0.13 (3.94)***
Non-adopters	(d) 0.52	(b) 0.63	TU = −0.11 (3.18)***
(iii) Depth of poverty			
Adopters	(a) 0.17	(c) 0.23	TT = −0.06 (2.04)**
Non-adopters	(d) 0.18	(b) 0.26	TU = −0.08 (2.21)**
(iv) Severity of poverty			
Adopters	(a) 0.08	(c) 0.14	TT = −0.06 (4.21)***
Non-adopters	(d) 0.11	(b) 0.15	TU = −0.04 (2.05)**

Note: Statistical significance at the 99 per cent (***), 95 per cent (**) and 90 per cent (*) confidence levels. T-statistics in parenthesis.

counterfactual scenarios. The last column of Table 7 presents the treatment effects of adoption of pigeonpea. We find the same qualitative results, where adoption significantly increases consumption expenditure and reduces the probability of being poor. Improved pigeonpea adoption increases consumption expenditure by about 31 percentage points compared to the non-adopters. For non-adopters, the mean per capita expenditure would have been increased by 29 percentage points had they adopted improved pigeonpea varieties. Head count index, poverty gap index and poverty severity index all suggest that adoption of improved pigeonpea technology has significant impact on reducing poverty among rural households in Tanzania.

These findings are consistent with recent studies on the impact of modern crop varieties on household welfare. Hossain et al. (2006) and Mendola (2007) in Bangladesh, Janaian et al. (2006) in India, and Wu et al. (2010) in China showed that the adoption of improved rice varieties has a significant positive impact on household income and a negative impact on poverty status. Becerril and Abdulai (2010) using propensity score matching methods found that improved maize adoption significantly increases per capita expenditure and reduces poverty in Mexico. Kijima et al. (2008) also showed that NERICA rice adoption reduces poverty without deterioration in income distribution in Uganda. Kassie et al. (2011) using PSM methods found that adoption of improved groundnut varieties in rural Uganda increases crop income and reduces poverty.

To gain further understanding of the impact of adoption on different groups of adopters, we also examined the differential impact of adoption by dividing households into quintiles based on farm size, education level and off-farm income. The stratification was made based on matched samples obtained from the single nearest neighbour matching estimator. (Results are reported in Table 8.) As observed in Table 8, the impact of adoption on consumption expenditure decreases with farm size. Interestingly, gain in consumption expenditure is highest in the lower farm-size quintiles (2 and 3), and 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. Similarly, the reduction in poverty is greater in the lowest farm-size quintiles (2 and 3). While the relationship between adoption and education does not show a clear pattern, the poverty reduction effect is greater in third education quintiles. These results suggest that poorer farmers and more educated farmers might benefit more from new agricultural technologies, and that providing farmers with basic education might enhance productivity.

Table 8. Differential impact of adoption by farm size, education and off-farm income

Stratified by farm size (quintiles)	Mean impact on household consumption	Mean impact on headcount ratio	Mean impact on depth of poverty	Mean impact on severity of poverty
1	0.317 (0.479)	0.016 (0.14)	−0.035 (0.35)	−0.040 (0.42)
2	1.074 (2.17)**	−0.171 (1.69)*	−0.222 (2.51)***	−0.241 (2.75)***
3	1.27 (1.93)*	−0.202 (1.99)**	−0.175 (1.87)*	−0.482 (1.97)**
4	0.732 (1.14)	−0.158 (1.29)	0.022 (0.21)	−0.034 (0.33)
5	0.610 (1.02)	−0.003 (0.03)	−0.133 (1.26)	−0.167 (1.62)
Stratified by education				
1	0.961 (1.52)	0.013 (0.14)	−0.089 (1.00)	−0.140 (1.55)
2	0.661 (1.48)	−0.031 (0.29)	−0.114 (1.22)	−0.145 (1.58)
3	1.415 (2.53)***	−0.117 (1.00)	−0.240 (2.47)***	−0.265 (2.80)***
4	0.505 (0.67)	−0.031 (0.29)	−0.110 (0.11)	−0.014 (0.13)
5	0.469 (0.79)	−0.049 (0.35)	−0.016 (0.14)	−0.038 (0.039)
Stratified by off-farm income				
1	−0.914 (1.15)	−0.008 (0.13)	−0.027 (0.037)	−0.041 (0.49)
2	0.299 (1.26)	−0.004 (0.09)	−0.055 (1.05)	−0.083 (1.36)
3	0.641 (3.56)***	−0.087 (1.29)	−0.200 (3.24)***	−0.223 (3.76)***
4	0.053 (0.19)	−0.089 (0.78)	−0.052 (0.83)	−0.023 (0.55)
5	0.413 (1.71)*	−0.139 (1.42)	−0.044 (1.75)*	−0.014 (1.66)

Notes: Statistical significance at the 99 per cent (***), 95 per cent (**) and 90 per cent (*) confidence levels. T-statistics in parenthesis.

Finally, we tried checking the sensitivity of the estimated average adoption effects to changes in the specification of the propensity score. Smith and Todd (2005) and Heckman et al. (1998) showed that matching estimates can be sensitive to variables chosen in the propensity score equation. We perform sensitivity checks by excluding potential endogenous covariates such as total cultivated land, household rented in land, and improved crop variety other than maize in the specification of the propensity score indicated in Table 5. The results are reported in the Online Appendix (Tables 2 and 3). The qualitative results remain the same as the previous findings. The estimates are obtained using the single nearest neighbour estimator. The matching estimates are reasonably robust to alternative propensity score specification, suggesting the positive significant effect of technology adoption on consumption expenditure and reducing the probability of being poor.

6. Conclusions

This article evaluates the impact of adoption of improved pigeonpea technologies on consumption expenditure and poverty status measured by headcount index, poverty gap index and poverty severity index in rural Tanzania. The study utilises cross-sectional farm household level data collected in 2008 from a randomly selected sample of 613 households in Tanzania. The causal impact of technology adoption is estimated by utilising propensity score matching and switching regression methods to assess the robustness of the results. 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 adopters has systematically different characteristics than the group of non-adopters. Second, both the propensity score matching and switching regression results suggests that adopters of improved pigeonpea have significantly higher consumption expenditure than non-adopters even after controlling for all confounding factors. The same results also show that adoption of improved pigeonpea technologies reduces poverty significantly. 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 also mean less poverty.

The question is if the poverty effects of new varieties are so great, what explains the lack of adoption by about 70 per cent of the surveyed households in Tanzania? As shown in earlier results, the sample adoption level for pigeonpea is about 33 per cent. The analysis of the determinants of adoption generated very interesting results. Inadequate local supply of seed and access to information about the new cultivars are key constraints for pigeonpea 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 pigeonpea 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.

The results presented in this article suggest that attention to improving the seed supply system for minor crops that are not likely to be attractive to the commercial seed sector, but which has significant welfare-enhancement potential for the poor. One possibility is public-private partnerships, with a particular focus on facilitating the growth of local commercial seed enterprise development, particularly since the overall size of the potential market is limited. Innovative means of improving the informal seed sector supply of improved varieties is also an important option (Audi et al., 2009), through the use of alternative certification systems such as truth-in-labelling systems. 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 commercialisation. 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 three to fiveyears. Strengthening the farmer-based seed production programme 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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Notes

1. The exchange rate at the time of the survey was about 1US$ = 1255 TSh (Tanzania Shilling).
2. The FIML estimates of the parameters of the endogenous switching regression model are obtained using the *movestay* command in STATA (Lokshin and Sajaia, 2004).

3. For the above calculations TSh 468 per person per day is used as the poverty line (HBS, 2007). This is the basic needs poverty line for Tanzania during the survey period (2007/2008). The food poverty line during the same year was TSh341 per person per day.
4. As prices of pigeonpea vary both across villages and through the extended harvest season and thus observed only for participants, we use lagged and average village prices.
5. In this article, the common support region is implemented, following the example of Leuven and Sianesi (2003), discarding observation from the adopters group, whose propensity score is higher than the maximum or less than the minimum propensity score of non-adopters.
6. The common support graph, covariate balancing test and ATT results are obtained using the Stata 11 pstest and psmatch2 commands, respectively (Leuven and Sianesi, 2003).
7. The FIML estimates of the endogenous switching regression model are not reported and can be available on request. Determinants of consumption expenditure and poverty are also not discussed since they are not the primary objectives of the article.

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