IMPROVED LEGUME SEED DEMAND SYSTEMS IN CENTRAL MALAWI: WHAT DO FARMERS' SEED EXPENDITURES SAY ABOUT THEIR PREFERENCES?

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Abstract

The overall objective of this paper is to assess the demand for improved groundnut, bean, and soybean seed in central Malawi. Specifically, it examines how smallholder farmers respond to changes in market prices of improved legume seed. It also assesses factors that affect the decision to participate in improved seed technology transfer. Considering four commodities namely groundnuts, beans, soybeans and maize, a staple food, the paper estimates a multivariate probit and a linear approximate of the Almost Ideal Demand System (LA/AIDS) using cross section data collected by ICRISAT in 2010. Uncompensated price and expenditure elasticities are reported for the LA/AIDS model. The paper finds high own price elasticities in all four commodities considered. It also indicates that land, household size and education levels affect participation in improved technology. Cross elasticities varied across the commodities considered. As pertain expenditure elasticities, farmers would increase expenditure on improved groundnut and beans if their incomes increased. The results also reveal that if farmers' incomes increase they would reduce soybean's expenditure share. The results generally show that farmers are very sensitive to changes in improved legume seed prices and incomes.

Key words: legumes, demand, LA/AIDS, multivariate probit

1. Introduction

In Africa, seed for legume crops is traditionally recycled by selecting desirable traits to be continued for the next cropping season. Most smallholder farmers grow recycled varieties. Recycled local varieties, despite having most of the desired attributes are, by far, low yielding and late maturing as compared to genetically improved varieties (Minde, 2008).With constraints of population growth and climate change, there is an incessant need for high yielding, early maturing and disease resistant cultivars. The problem is, on the one hand, that farmers do not have the technical know-how to breed cultivars with the desired attributes. On the other hand, the private sector shuns production of seed for legumes because they are bulky and incur high transportation costs. Therefore, the role of legume seed production lies with government and research institutions (Minot, 2007).

In Malawi, legume seed breeding is done by the International Crops Research Institute for the Semi Arid-Tropics (ICRISAT) and International Center for Tropical Agriculture (CIAT) in collaboration with the Department of Agricultural Research. ICRISAT is concerned with groundnuts while CIAT with beans. Seed production is done by carefully selected farmers organized in seed multiplication groups. When seed is multiplied, it is sold back to ICRISAT and CIAT at a profit. Then the research institutions sell the seed either to government, private firms, non-governmental organizations or individuals. Groundnut seed moves along the marketing channel from the producers (seed breeders and multipliers) to the final consumer – the smallholder farmer (Siambi, *et al.*, 2009).

This study was commissioned by ICRISAT Malawi to assess the nature of demand for groundnut seed. We include beans and soybeans because they are also commonly grown legumes in the study area and might possibly compete with groundnuts. We have also included maize, a cereal crop which is mainly grown as a staple food and is usually intercropped with the aforementioned legumes. Usually, farmers prefer allocating land to maize to meet their subsistence food requirements before they allocate it to other potential cash crops. Therefore, the study could have been biased if we left maize out of the seed demand system.

In order to understand the nature of seed demand, it is important to realize that farmers are consumers of legume seed technologies. Thus the market price of seed reflects not only the costs associated with breeding and production but also farmers' preferences of particular varieties. To capture these preferences, there is need to analyze demand from the marketing side.

Noteworthy, several adoption studies in Malawi have pointed out that improved groundnut adoption rates are low with the exception of the CG7 variety (Minot, 2007; Minde, *et al.*, 2008; Monyo *et al.*, 2010; Simtowe *et al.*, 2010a 2010b). Similar cases have been reported for beans and soybeans. Despite their importance in agricultural policy analysis, adoption studies have, however, not addressed the issue of how farmers' seed purchases change with respect to changes in improved seed's own price, other crops' seed prices and farmers' incomes. Furthermore, much less is known about market places, in general, and very few citations discuss characteristics of seeds, product quality, homogeneity, market transactions and demand for products and inputs (Lipper *et al*., 2009).

Knowing farmers' responsiveness to market outcomes may assist in providing policy recommendations pertaining to seed supply. Furthermore, based on farmers' seed expenditure patterns, it is possible to derive a demand system for seed technologies. By estimating elasticities of the demand system, it is possible to reliably inform market chain participants such as breeders, seed multipliers, distributors and agricultural input policy makers on how seed demand responds to changes in its market determinants and farmer circumstances.

Overtime, demand for agricultural commodities has been analyzed using single equation and multiple equations such as linear expenditure, Rotterdam and Almost Ideal Demand Systems (AIDS) (Málaga and Williams, (2000). Out of these models, the Almost Ideal Demand System (AIDS) is the most preferred model for estimating demand systems. It is widely acclaimed for its satisfaction of homogeneity, adding up and symmetry restrictions. Aggregating perfectly over consumers without invoking parallel linear Engel curves, the AIDS model also satisfies the axioms of choice exactly. Further, it has a functional form which is consistent with known household-budget data and it is simple to estimate, largely avoiding the need for non-linear estimation**.** Although many of the desirable properties are possessed by one or other of the

Rotterdam or translog models, neither possesses all of them simultaneously (Deaton & Muellbauer, 1980).

The AIDS model has mostly been applied to food products such as meat, fish, vegetables, milk and cereals. Fadhuile *et al.*, (2011) used the Linear Approximation of the AIDS (LA/AIDS) to estimate demand for pesticides in France while Alboghdady and Alashry, (2010) used it in assessment of demand systems in Egyptian meat products.

Noting the caveats of selection bias and potential endogeneity from the data, the study firstly analyzes determinants of improved legume seed participation using a multivariate probit procedure following Capellari and Jenkins, (2003). From the probit analysis, an Inverse Mills Ratio is computed and used in the subsequent demand equations to make inference about changes in the population when changing the explanatory variables (Wooldridge, 2009). Then it estimates LA/AIDS model specification to estimate demand elasticities with respect to smallholder farmers' groundnut, beans soybean and maize seed expenditure in Central Malawi.

2. Determinants of Participation: Multivariate probit

In order to address the first objective i.e. the factors that influence the decision to participate in improved groundnut and pigeon pea farming and to correct for selection bias resulting from zero expenditure, a selection model is required. We start our estimation with a probit model. The probit model is used because its likelihood function is well behaved as it gives consistent Maximum Likelihood Estimate (MLE) coefficients (β) and standard error of the estimate (s) (Maddala, 1992).The probit model estimates the probability of participating in improved seed technologies for household level data and measures this likelihood after controlling the relevant variables used in the model. The dependent variable in the first step is defined as a dichotomous variable with the values 1 for participants and 0 for non-participants.

It should be noted that since the demand model that follows requires data for other crops it is also important to estimate participation equations for those variables. The simplest and most straight forward estimation procedure would be to estimate each probit equation separately. However, it is important to notice that the data for different crops is collected from the one individual at a given point in time. This may bring endogeneity within the data set i.e. the error terms between the equations of different crops might be correlated since data is being collected from the same individual whose decision on a particular variety choice may affect the probability of selecting another variety. As such we need to use a multivariate probit model to address this problem. Following Cappellari and Jenkins, (2003) the multivariate probit model is structured as follows. Consider the M-equation multivariate probit model:

$$y_{im}^* = \beta_m{}' X_{im} + \epsilon_{im}, m = 1, \dots, M$$

$$y_{im}^* = 1 \; if \; y_{im}^* > 0 \; and \; 0 \; otherwise \tag{1}$$

$\epsilon_{im}, m = 1, \dots, M$ are error terms distributed as multivariate normal, each with a mean of zero, and variance-covariance matrix V, where V has value of 1 on the leading diagonal and correlations $\rho_{jk} = \rho_{kj}$ as off diagonal elements. The multivariate probit model has a structure like the Seemingly Unrelated Regression (SUR), except that the dependent variables are binary indicators. The y_{im} might represent outcomes for *M* different choices at the same point in time, for example, whether a farmer cultivates *M* varieties of crops. The X_{im} is a vector of explanatory variables and β_m are unknown parameters to be estimated. The probability function of the probit model is usually the standard normal density which provides predicted values within the range (0, 1).

The multivariate probit model is estimated by simulated maximum likelihood. The log-likelihood function for a sample of *N* independent observations is given by

$$L = \sum_{i=1}^{N} w_i \log \Phi_m (\mu_i; \Omega) \tag{2}$$

Where w_i is an optional weight for observation $i = 1, \dots, N$, and $\Phi_m(.)$ is the multivariate standard normal distribution with arguments μ_i and Ω where $\mu_i = (K_{im}' X_{im})$ with $K_{ik} = 2y_{ik} - 1$, for each I $k = 1, \dots, m$. Matrix Ω has constituent elements Ω_{jk} where

$$\Omega_{jj} = 1 \; for \; j = 1, \dots, m$$

$$\Omega_{21} = \Omega_{12} = K_{i1} \, K_{i2} \, \rho_{21}$$

$$\Omega_{31} = \Omega_{13} = K_{i3} \, K_{i1} \, \rho_{31}$$

$$\Omega_{jk} = \Omega_{kj} = K_{im}\, K_{im-1}\, \rho_{mm-1}$$

As shown the log-likelihood function depends on the multivariate standard normal distribution function $\Phi_m(.)$. In this research, the Geweke–Hajivassiliou–Keane (GHK) smooth recursive conditioning simulator will be applied to evaluate the multivariate normal distribution function (Borsch-Supan *et al.* 1992; Borsch-Supan and Hajivassiliou, 1993; Keane, 1994; and Hajivassiliou and Ruud, 1994). The GHK simulator exploits the fact that a multivariate normal distribution function can be expressed as the product of sequentially conditioned univariate normal distribution functions, which can be easily and accurately evaluated.

From equation 2 an Inverse Mills Ratio (IMR) is further computed. The IMR in this case is calculated from the aggregate model i.e. the model that describes general participation into improved legume seed. The inverse mills ratio is

$$IMR = \hat{\lambda} = \frac{\Phi(\beta' x)}{[1-\Phi(\beta' x)]} \tag{3}$$

During the second stage the Inverse Mills Ratio is taken as an explanatory variable in the demand function.

To increase the model's efficiency, Vassilopoulos *et al.*(2006) suggests an extension of the above model which uses all observations in the second step of the estimation, and modifies the IMR for zero observations as:

$$IMR = \hat{\lambda} = \frac{-\varphi(\beta' x)}{[1-\Phi(\beta' x)]} \tag{4}$$

It should be noted that the second model is usually heteroscedastic and therefore its variance covariance matrix needs to be corrected. The Murphy and Topel (1985) is applied (see appendix).

The coefficients from the probit model and the marginal effects enable us test the first hypothesis that socio-economic factors and demographic factors do not affect participation in improved groundnut and pigeon pea seed.

3. Almost Ideal Demand System (AIDS)

Most demand models start with specification of an arbitrary direct or indirect utility function or cost functions (Christensen *et al.*, 1971). However, the Almost Ideal Demand System starts from a specific class of preferences which permit exact aggregattion over consumers. They present market demands as if they were the outcome of decisions by a rational representative consumer. Such preferences are known as Price Independent Generalized Logarithmic (PIGLOG). They are represented via the cost or expenditure function. This function defines the minimum expenditure necessary to attain a specific utility level at given prices (Deaton & Muellbauer, (1980); Green &Alston (1991) and Buse, (1994). Denoting the expenditure function as $c(u, p)$ for utility u and price vector p, our PIGLOG class can be defined as

$$\ln c(u, p) = u \ln b(p) + (1 - u) \ln a(p) \tag{5}$$

where $\alpha_i(p) = (a_i \ln b - b_i \ln a)/(\ln b - \ln a)$ and $\beta_i(p) = b_i/(\ln b - \ln a)$ for $a_i = \partial \ln a/\partial \ln p_i$ and $b_i = \partial \ln b/\partial \ln p_i$. This equation gives the expenditure function as a utility weighted geometric mean of the linear homogeneous functions $a(p)$ and $b(p)$ representing the cost functions of the very poor and $(u = 0)$ and the very rich $(u = 1)$ respectively. The full demand systems within the Worker-Lesser class can be generated by a suitable choice of of the functions *b(p)* and *a(p)* (Deaton & Muellbaur, 1986). In the next step, we specify functional forms for $\ln a(p)$ and $\ln b(p)$. To ensure flexibility in the functional form, we ensure that the functional form has enough parameters so that at any single point, its derivatives$\frac{\partial c}{\partial p_i}, \frac{\partial c}{\partial u}, \frac{\partial^2 c}{\partial p_i \partial p_j} \frac{\partial^2 c}{\partial u \partial p_i}, \frac{\partial^2 c}{\partial u^2}$, can be set equal to its arbitrary cost functional form (Deaton & Muellbauer, 1980). Let

$$\ln a(p) = a_o + \sum \alpha_k \ln p_k + \frac{1}{2} \sum_k \sum_m \gamma_{km}^* \ln p_k \ln p_m \tag{6}$$

$$\ln b(p) = \ln a(p) + u\beta_0 \prod_{\mathrm{k}} p_k^{\beta_k} \tag{7}$$

By combining (2) and (3) the “Almost Ideal Demand System (AIDS)” cost function becomes

$$\ln c(u,p) = \alpha_0 + \sum_k \alpha_k \ln p_k + \frac{1}{2}\sum_k \sum_m \gamma^*_{km} \ln p_k \ln p_m + u\beta_0 \prod_{\mathrm{k}} p_k^{\beta_k} \tag{8}$$

Noteworthy, the cost function $c(u,p)$ is lineary homogeneous in p . This makes it a valid representation of preferences. The choice of (2) and (3) leads to a system of demand equations with desirable properties. We derive our demand functions from (4) using the Shephard's Lemma i.e.

$$\frac{\partial c(u,p)}{\partial p_i} = q \tag{9}$$

Then multiplying both sides of (5) by $\frac{p_i}{c(u,p)}$ converts to elasticity getting

$$\frac{\partial c(u,p)}{\partial p_i}\frac{p_i}{c(u,p)} = \frac{\partial \log c(u,p)}{\partial \log p_i} = \frac{p_i q_i}{c(u,p)} = w_i \tag{10}$$

where w_i is the budget share of good *i*. this implies that the logarithmic differentiation of (4) gives budget shares as a function of prices and utility as follows:

$$w_i = \alpha_i + \beta_i u\beta_0 \prod_{\mathrm{k}} p_k^{\beta_k} + \sum_j \gamma_{ij \ln p_j} \tag{11}$$

Where $\gamma_{ij} = \frac{1}{2}\left(\gamma^*_{ij} + \gamma^*_{ji}\right)$

We assume that the smallholder farmer in question is a utility maximizing consumer of seed technologies. The farmer's total expenditure *x* equals $c(u,p)$. Inverting the equality to give *u* as a function of of *p* and *x* gives the indirect utility function. Then doing this in (4) and substituting the result in (7), we get the budget shares as a function of *p* and *x* as shown in (8)

$$w_i = \alpha_i + \beta_i \ln(\frac{X}{P}) + \sum_j \gamma_{ij \ln p_j} \tag{12}$$

$$\ln P = \alpha_0 + \sum \alpha_k \ln p_k + \frac{1}{2}\sum_k \sum_m \gamma^*_{km} \ln p_k \ln p_m \tag{13}$$

where ln P is the price index and

$$\gamma_{ij} = \frac{1}{2}\left(\gamma^*_{ij} + \gamma^*_{ji}\right) \tag{14}$$

4. Estimation

Deaton and Muellbauer (1980) reported that it was difficult to estimate the price index reported in equation (9). As such, they suggested a linear approximation of the AIDS model using Stone's price index. In this case, a linear price index is specified by

$$\ln P = \sum_{i=1}^{n} w_i \ln p_i \tag{15}$$

Using the linear price index gives rise to the linear approximate of the AIDS model (LA/AIDS) model. The paper employs the linear approximate of the AIDS model to assess demand of seed commodities in question.

The basic demand restrictions namely adding up, homogeneity, and symmetry are expressed in terms of the system's coefficients as follows:

1. Adding up: $\sum_{i=1}^{n} \alpha_i = 1$; $\sum_{i=1}^{n} \beta_i = 0$; $\sum_{i=1}^{n} \gamma_{ij} = 0$; $\sum_{i=1}^{n} w_i = 1$
2. Homogeneity: $\sum_{i=1}^{n} \gamma_{ij} = 0$
3. Symmetry: $\gamma_{ij} = \gamma_{ji}$

Green & Alston (1990) disputed that when the linear approximation of the AIDS model is used, it results and elasticities of the AIDS model are used, the results are incorrect. They therefore presented correct formulas for the LA/AIDS model and provided methods of correcting the errors resulting from using elasticities from the AIDS model. This paper uses the correct formulas they suggested to compute uncompensated elasticities. The uncompensated price elasticity for good *i* with respect to good j is

$$\eta_{ij} = -\delta_{ij} + \frac{\gamma_{ij}}{w_i} - \frac{\beta_i}{w_i}\{w_j + \sum_k w_k \ln P_k(\eta_{kj} + \delta_{kj})\} \tag{16}$$

The income elasticity for commodity *i* is given by

$$e_i = \frac{\beta_i}{w_i} + 1 \tag{17}$$

The seed demand system estimated in this study involves four seed with their repsective prices and expenditures. The system estimated involves four equations namely:

$$gnuts = \alpha_0 + \beta_{i1} \ln pgnut + \beta_{i2} \ln pbns + \beta_{i3} \ln psoy + \beta_{i4} \ln pmz + \delta_1 \ln \text{expend} + \mu_1$$

$$wbns = \alpha_0 + \beta_{i1} \ln pgnut + \beta_{i2} \ln pbns + \beta_{i3} \ln psoy + \beta_{i4} \ln pmz \ + \delta_2 \ln expend + \mu_2$$

$$wsoy = \alpha_0 + \beta_{i1} \ln pgnut + \beta_{i2} \ln pbns + \beta_{i3} \ln psoy + \beta_{i4} \ln pmz \ + \delta_2 \ln expe\,nd + \mu_3$$

$$wmaize = \alpha_0 + \beta_{i1} \ln pgnut + \beta_{i2} \ln pbns + \beta_{i3} \ln psoy + \beta_{i4} \ln pmz \ + \delta_2 \ln expend + \mu_4$$
(18)

The variables used are defined in Table 1. α_0, β_{ij}, and δ_i are unknown parameters to be estimated; μ_i is the error term of the ith equation. With homogeneity, symmetry and adding up restrictions imposed, the system of equations in (14) was estimated jointly using Zellner's Semingly unrelated regressions. All analysis was done using Stata 10.

4. Data

4.1.Description of the study area and data collection time

The data used for this study was collected in a household survey conducted by ICRISAT between December, 2010 and January, 2011. Being time for planting, it was deemed the appropriate time to collect seed expenditure data. The data was collected in Mchinji District. Specifically the data was collected from Mkanda and Tembwe Extension Planning Areas. Mchinji was chosen because it produces a comparatively large amount of groundnuts than other districts in the central region (Simtowe *et al*. 2010b). Mchinji lies within Lilongwe Agricultural Development Division (ADD) in the central region on an altitude of about 600 metres above sea level. The central region has warm to hot weather and cloudy with light to heavy rains, rainy season from November to March. This type of rainfall supports, crops such as groundnuts that are planted early in the growing season (Edriss, 2003a).

4.2.Data Collection tools and methods

Firstly, two extension planning areas (EPAs) were randomly selected in Mchinji district. These were Tembwe and Mkanda EPAs. From these EPAs, a list of all villages was taken. The villages were listed along with their populations. Noting that the strata were not proportional to the actual population, we employed the Probability Proportional to Size (PPS) sampling. Probability Proportional to Size (PPS) sampling was used because it produces a cost effective, representative and self weighted sample (Edriss, 2003b). Having listed the populations of each randomly sampled village, we calculated their cumulative populations. Then using the total cumulative population divided by the number of strata (30 villages) sampled, we calculated our sampling interval (670). Using a random number, equal to or less than sampling interval, we located the first village whose population exceeded the random number. We added the sampling interval to the random number. Then we choose a village whose cumulative population exceeded that number. That way we were able to determine the next village. We repeated the procedure until we found the total number of villages we desired.

The study covered 22 villages and 170 farming households. The sample size of 170 households was calculated by considering the estimated population proportion ($p > 85\%$) involved in groundnut production, the desired degree of confidence ($z = 1.96$) and the absolute size of the of the error in estimating p we were willing to accept ($e = 5\%$) and considering 10% non respondents. Semi structured questionnaires were used in data collection.

4.3.Variable description and descriptive statistics

Variables used in the system estimation, definitions, expected signs and their descriptive statistics are presented in Table1 below.

Table 1: Factors that affect improved seed demand

Characteristic	Non-adopter	Adopter	Total	Difference
Demographic factors				
Proportion of female farmers	0.4236	0.4056	0.4116	0.0180
Age	43.7291	37.7832	39.7744	5.9460***
Household size	4.9861	5.2273	5.1465	-.2412
Area under cultivation	5.8354	13.2488	10.7662	-7.4134***
Value of assets	17547.94	35002.8	29157.45	-17454.87***
Education				
Years spent in school	3.9027	5.5489	4.9977	-1.6462***
Institutional factors				
Contacts with government extension	2.2618	2.2496	2.2537	.0123
Contacts with NGO extension worker	1.1471	.9115	.9905	.2356
Membership in a farmer’s club (%)	34.04	30.50	31.68	2.26
Distance to the main market (km)	3.2215	3.2247	3.2237	-.0032

Note: ***p<0.01 **p<0.05 *p<0.1

Table 2: Variable Definitions and Descriptive Statistics.

Variable	Definition	Transformation	Mean	Std. Dev.	Expected sign
wgnut	Share of groundnut	None	0.091	0.047	+
wbns	Share of beans	None	0.174	0.013	+
wsoy	Share of soy	None	0.026	0.007	+
wmaize	Share of maize kg^{-1}	None	0.073	0.014	+
pgnut	Price of groundnut MWK kg^{-1}	Natural log	114.388	17.844	+/-
pbns	Price of beans MWK kg^{-1}	Natural log	167.321	7.838	+/-
psoy	Price of soy MWK kg^{-1}	Natural log	52.488	5.134	+/-
pmz	Price of maize MWK kg^{-1}	Natural log	126.747	4.407	+/-
expe	Expenditure in MWK	Natural log	114.388	17.844	+/-

The exchange rate at the time of survey was USD 1.00= MWK150.00

Source: Author's calculations, 2012

5. Empirical Results

5.1.Multivariate Probit

The multivariate probit model presented as equation 1 was estimated to identify factors that affect the decision to participate in groundnut, pigeon pea, beans, soybean and maize farming. The model had a log likelihood of -1292. It also had a Wald chi-square equal to 111.57 which was significant at 1 percent. The hypothesis that the correlations between the error terms in the participation equations were equal to zero was rejected at 1 percent implying that there was endogeneity within the data. This endogeneity was corrected using a simulation method for evaluating multivariate normal distribution functions known as the Geweke–Hajivassiliou–Keane (GHK) smooth recursive conditioning simulator (Borsch-Supan *et al.* 1992; Borsch-Supan and Hajivassiliou, 1993; Keane, 1994; and Hajivassiliou and Ruud, 1994). The diagnostic statistics imply that the model had fitted correctly. Robust standard errors are used to correct for heteroscedasticity. Results of the multivariate probit model are presented in Table 3 and marginal effects are reported in table 4.

5.1.1. Household size

Tables 3 and 4 show that household size was positive in the aggregate, groundnut and pigeon pea participation equations. Household size positively and significantly influences the decision to use improve seed in groundnut and pigeon pea. The coefficient for the aggregate model is significant at 10 percent. The marginal effect of 0.1019 suggests that if household size increases by one individual, the probability of participating in improved seed would increase by 0.1019. In the groundnut and pigeon pea equations, the marginal effects of 0.0291 and 0.1669 suggests that increasing household size by one individual increases the probability of participation by 0.0291 and 0.1669 respectively.

In rural areas, large households provide labour on the farm as such it is likely that farmers who have large families would provide the necessary labour to cultivate improved seed (Simwaka, et al., 2011). This finding corresponds with Simtowe et al. (2010) and Mendola (2007) who consistently found evidence that participation increases with household size among smallholder farmers in Malawi and rural Bangladesh, respectively.

5.1.2. Education level of the household head

Education of the household head positively influences participation in improved technology. In the aggregate model, education was significant at 1%. Similarly, groundnut, pigeon pea and bean equations showed statistical significance as shown in Table 6.2. Nevertheless, in maize and soybean, education was not statistically significant.

The positive marginal effects in all variables indicate increasing participation with every additional year of education. For instance, in the aggregate model, a marginal effect of 0.0580 implies that if an individual adds one more year in school the probability of participating in improved seed technology would increase by 0.0580. An additional year in school increases the probability of participation in improved groundnut by 0.0385, in pigeon pea by 0.0315 and in improved beans by 0.0429. This implies that education of the household head increases the probability of using improved seed. This finding corresponds with Giné & Yang (2008) and Zeller, Diagne, & Mataya (1997) who also found that education increases participation in improved technology in Malawi.

5.1.3. Cultivated land

Land is a constraining factor of production. In Malawi, the national average land holding size is 1.5 hectares and highly skewed to the left (NSO, 2011). In the aggregate model, land cultivated positively and significantly influences participation. The marginal effect of 0.0103 indicates that if land cultivated increases by 1 hectare, farmers' probability of participating in improved seed technology transfer would increase by 0.0103.

The amount of land cultivated is positive and significant at 10 percent in the pigeon pea equation. It had a marginal effect of 0.0068 indicating that the more land an individual possesses the more likely they would participate in improved pigeon pea farming.

Similarly, the coefficient for the amount of land cultivated was positive and significant at 5 percent in the groundnut equation. The marginal effect for land was 0.0086 which means that if land increased by one acre, the probability of participation in groundnut seed technology would increase by 0.0086 percentage points. Kassie et al. (2010) also found a significant positive relationship on participation in improved groundnut in Uganda.

In the bean equation, the amount of land had a positive and significant sign at 5 percent. It had a marginal effect of 0.0039 meaning that if the amount of land cultivated increased by one hectare the probability of participating in technology transfer of bean seed would increase by 0.0039 percentage points. This finding is consistent with Ayalew (2011) who found a positive relationship in haricot beans in Ethiopia.

The findings in this study correspond with Rahman (2004) who found that the more land a farmer has, the more likely that they would adopt improved technology in Asia. Simtowe & Zeller (2007) also found increasing participation in maize farmers who had land than those who were landless. Khandker, Koolwal, &Samad (2010) found that land was an important determinant of participation in several programs.

5.1.4. Age of the Household Head

Age of the household head is a key determinant of participation in technology adoption. In Malawi, most of the population falls within the economically active age group of14 to65

(International Labour Organization, 2012). In this study, age of the household head contributes significantly to improved seed technology participation. It has 10 percent statistical significance in the aggregate model. Nevertheless, the marginal effect for age in the aggregate model implies that the probability of participation decreases by 0.0064 for every additional year a household head adds above the mean.

The variable was not significant in the groundnut, pigeon pea, soybean and maize equations but was significant at five percent in the bean equation. The marginal effect for beans indicates that for every additional year above the mean, the probability to participate decreases by 0.0072. Moreover, the introduction of this variable in a quadratic form highlights a bell-shaped relation with a reversal of the curve around 37 years. This finding is in agreement with Ntsama and Kamgnia (2008) who found a quadratic relation with participation in maize. This is also consistent with Kafle and Shah (2006) who also found that age was significant at 10 percent in their improved potato adoption study. Further, the sign of the coefficient in maize is consistent with Idrisa, Ogunbameru and Shehu (2012) who found increasing probability of participation with age in improved maize in Nigeria.

In sum, factors that determine participation into improved seed technology include household size, education level of the household head, amount of land cultivated and age of the household head.

Table 3 : Determinants of participation in improved seed technology

Variable	(1) Aggregate	(2) Pigeon pea	(3) Groundnut	(4) Beans	(5) Maize	(6) Soybean
Gender	-0.0569	0.0121	-0.0648	-0.0765	0.0229	0.158
	(0.130)	(0.134)	(0.137)	(0.136)	(0.128)	(0.126)
	-0.0757	-0.306**	0.136	-0.0330	-0.0314	-0.0183
Club membership	(0.135)	(0.141)	(0.145)	(0.147)	(0.138)	(0.135)
Education level of	0.0581***	0.0315*	0.0385**	0.0429**	0.0148	0.0105
head	(0.0170)	(0.0178)	(0.0175)	(0.0184)	(0.0172)	(0.0170)
	0.0103**	0.00683*	0.00863**	0.00829**	0.00234	0.00392
Land cultivated	(0.00419)	(0.00397)	(0.00405)	(0.00392)	(0.00340)	(0.00363)
Age of head	-0.00641	-0.00310	-0.00191	-0.0072**	0.000116	0.00328
	(0.00399)	(0.00317)	(0.00303)	(0.00353)	(0.00305)	(0.00324)
	0.00204	0.0134	-0.0245	-0.0177	0.0153	-0.0262
Contacts by extension	(0.0160)	(0.0221)	(0.0207)	(0.0241)	(0.0173)	(0.0177)
Distance to main	-0.00543	-0.00826	-0.0426*	-0.0419*	0.0449	0.00859
market	(0.0223)	(0.0255)	(0.0247)	(0.0247)	(0.0250)	(0.0254)
	0.102*	0.167**	0.0291	-0.0146	-0.0436	-0.00939
Household size	(0.0599)	(0.0651)	(0.0638)	(0.0668)	(0.0674)	(0.0675)
age2[3]	-0.0005	0. 325	-0. 324	0.0519	0.196	-0. 218
	(0. 467)	(0.404)	(0.4000)	(0. 435)	(0. 381)	(0. 396)
Constant	-0.270	-0.978**	-0.156	0.437	-0.0620	-0.176
	(0.371)	(0.396)	(0.395)	(0.412)	(0.397)	(0.396)
Observations[1]	423	423	423	423	423	423
Log likelihood	-1292	-1292	-1292	-1292	-1292	-1292
chi2	111.6	111.6	111.6	111.6	111.6	111.6

[3]On Age2 the coefficients and standard errors were multiplied by 10000 for presentation purposes i.e. to show that the numbers are not zeros. [1] Note: The observations across variables were collected from the same individuals i.e. the same farmer could possible grow all crops considered. There were no distinct groups per crop. That is why the sample size N does not vary.

Table 4: Marginal Effects after Multivariate Probit

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Aggregate	Pigeon pea	Groundnut	Beans	Maize	Soybean
Gender	-0.0569	0.0120	-0.0648	-0.0765	0.1584	0.0229
	(0.1304)	(0.1336)	(0.1369)	(0.1360)	(0.1262)	(0.1277)
Age	-0.0064*	-0.0030	-0.0019	-0.0072**	0.0033	0.0001
	(0.0040)	(0.0031)	(0.0030)	(0.0053)	(0.0032)	(0.0031)
Age2	-0.00005	-. 3250	-0.324	0. 0052	-0.0196	0. 2180
	(0. 467)	(0.404)	(0.4000)	(0. 435)	(0. 381	(0. 396)
Household size	0.1019**	0.1669***	0.0291	-0.0145	-0.0094	-0.0436
	(0.0598)	(0.0650)	(0.0638)	(0.0668)	(0.0675)	(0.0674)
Education of the	0.0580***	0.0314*	0.0385**	0.0429**	0.0105	0.0148
household head	(0.0170)	(0.0178)	(0.0175)	(0.0184)	(0.0170)	(0.0172)
Cultivated land	0.0103**	0.0068	0.0086**	0.0083**	0.0039	0.0023
	(0.0042)	(0.0040)	(0.0041)	(0.0039)	(0.0036)	(0.0034)
Contacts by	0.002	0.0134	-0.0245	-0.0177	-0.0262	0.0153
extension	(0.0159)	(0.0221)	(0.0207)	(0.0241)	(0.0177)	(0.0173)
Club membership	-0.0757	-0.3064**	0.1360	-0.0330	-0.0183	-0.0314
	(0.1346)	(0.1407)	(0.1447)	(0.1473)	(0.1353)	(0.1380)
Distance to main	-0.0054	-0.0083	-0.0426*	-0.0419*	0.0085	0.0449*
market	(0.0223)	(0.0254)	(0.0247)	(0.0247)	(0.0254)	(0.0250)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.2.LA/AIDS model

The model was estimated using Zellner (1962) iterative Restricted Seemingly Unrelated Regression (RSUR) in STATA 10. In estimation, the restrictions in the model led to a singular variance/covariance matrix of the errors as Alboghdady and Alashry, (2010) found. Therefore, to avoid the singularity problem, one of the share equations was arbitrary dropped from the system, the maize share equation. The coefficients from the potato equation were recovered using homogeneity, symmetry and adding up restriction. Results of the SUR model are presented in Table 2.

Generally, the results indicate that the model was well specified as most of the coefficients of determination were able to explain over 50 per cent of the variation in the model. Furthermore, the chi-square goodness of fit measures were statistically significant at 1 percent. As Table 2 also shows, most of the parameters in the system have retained the hypothesized signs making economic interpretation possible. Furthermore, all own price coefficients are significant at 1%. Elasticities of the demand system are presented in Table 3.

Table 5: The parameters estimates of the LA/AIDS model with homogeneity and symmetry restrictions

Regressors	Groundnut	Beans	Pigeon pea	Maize
Price	**-0.073*** **			
Groundnut	**(0.012)**			
Price Beans	0.040***	**-0.016*** **		
	(0.009)	**(0.009)**		
Price pigeon	0.036**	0.000	**--0.046*** **	
pea bean	(0.005)	(0.003)	**(0.007)**	
Price Maize	-0.003	-0.025***	0.010	**-0.619*** **
	(0.012)	(0.007)	(0.008)	**(0.036)**
Expenditure	0.214***	0.161***	0.029***	-0.240***
	(0.019)	(0.16)	(0.006)	(0.014)
IMR	-0.078***	-0.140***	-0.030***	0.073***
	(0.014)	(0.014)	(0.003)	0.007
Constant	-2.035***	-1.387***	0.246***	2.632***
	(0.200)	(0.278)	(0.064)	(0.143)
Chi-square	329.31***	214.49***	241.20***	848.65***

Note: ***p<0.01 **p<0.05 *p<0.1

Standard errors are in parentheses

Source: Author's calculations, 2011

Table 6: Calculated uncompensated (Marshallian) elasticities of the LA/AIDS model

	Groundnut	Beans	Soy bean	Maize
Groundnut	**-11.714**	3.013	5.818	4.711
Beans	0.997	**-4.548**	5.329	5.471
Soy bean	0.581	0.771	**-5.523**	0.563
Maize	-0.820	2.253	1.610	**-8.249**
Expenditure	2.862	0.583	-0.379	0.001

The bold values are own price elasticities. Others are cross price elasticities.

Source: Author's calculations, 2011

5.3.Estimation of Marshallian elasticities

The estimates of Marshallian own-price elasticities and expenditure elasticities are presented in Table 3. The own-price elasticities are negative as expected from theory. All seed commodities in question have highly elastic own price elasticities. Noteworthy, groundnut seed has the highest price elasticity (-11.71) followed by maize seed (-8.25) then soybean (-5.52). The lowest price elasticity was observed in beans (-4.55). As noted, the price elasticities of demand for marketed seed which is usually distributed by agro-dealers and the government parastatal ADMARC are high. The possible explanation for this phenomenon is that the marketed seed products are regarded expensive by most smallholder farmers (Mkandawire *et al*. 2001; Moyo, 2010). As Minot (2007) observed, farmers opt for other sources of seed that are not market based such as seed recycling and gift based exchange.

Considering cross price elasticities, the results reveal that improved groundnut seed has a substitutive relationship with soy (0.58). Groundnut and bean cross price elasticity showed an almost unitary relationship with groundnut (0.997) but complementary relationship with maize seed. Beans showed a less than unitary substitutive relationship with soy (0.77) and greater than unitary substitution with maize (2.25). Soybean had a substitutive relationship with all seed commodities in question.

Expenditure elasticities show that at as incomes increase by 10% farmers would increase expenditure on improved groundnut seed by 29%. Similarly, if their incomes increased by 10% they would also increase their expenditure shares on beans by 5.8%. However, if farmers' incomes increase by 10%, they would reduce soybean's expenditure share by 3.8%. This observation may be true because over the past half a decade, soybean as a farm output has not been fetching good prices on the market. Maize, being a staple food, is almost perfectly inelastic to changes in expenditure.

6. Conclusions

Using survey data collected by ICRISAT in 2010, the paper used a multivariate probit model linear approximation of the Almost Ideal Demand System (LA/AIDS) to assess demand for improved seed of groundnuts, beans and soybeans. The study included maize because the aforementioned legume seed commodities are usually intercropped with maize. The study aimed at estimating determinants of participation in improved seed technology. It estimated uncompensated own price, cross-price and expenditure elasticities of the commodities in question.

Factors that determine participation into improved seed technology include household size, education level of the household head, amount of land cultivated and age of the household head. However, determinants of participation varied from crop to crop.

The paper finds compelling evidence that small proportionate changes in own prices of improved legumes lead to greater than unitary proportionate changes in their purchases. This reveals that farmers have several options to choose from when improved seed prices rise on the market. The results reveal that improved groundnut seed has a substitutive relationship with soybeans. Groundnut and bean cross price elasticity showed an almost unitary relationship with groundnut but groundnut showed complementary relationship with maize seed. Beans showed a less than unitary substitutive relationship with soy and an elastic substitution with maize. Soybean had a substitutive relationship with all seed commodities in question.

As pertain expenditure elasticities, farmers would increase expenditure on improved groundnut seed by 29% if their incomes rise by 10%. If their incomes increased by 10% they would also increase their expenditure shares on beans by 5.8%. The results also reveal that if farmers' incomes increase by 10%, they would reduce soybean's expenditure share by 3.8%.

The results generally show that farmers are very sensitive to changes in improved legume seed prices and incomes. The major implication of the findings is that any intervention to improve farmers' seed purchases should take into account efforts to increase farmers' purchasing power. Subsidizing seed products may be one of the ways to achieve this.

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