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Determinants of Agricultural Technology adoption: the case of improved groundnut varieties in Malawi

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ABSTRACT

This paper applies the Average Treatment Effect (ATE) framework on data obtained from a random cross-section sample of 594 farmers in Malawi to document the *actual* and *potential* adoption rates of improved groundnut varieties and their determinants conditional on farmers' awareness of the technology. The fact that not all farmers are exposed to the new technologies makes it difficult to obtain consistent estimates of population adoption rates and their determinants using direct sample estimates and classical adoption models such as probit or tobit. Our approach tries to control for exposure and selection bias in assessing the adoption rate of technology and its determinants. Results indicate that only 26% of the sampled farmers grew at least one of the improved groundnut varieties. The potential adoption rate of improved groundnut for the population is estimated at 37% and the adoption gap resulting from the incomplete exposure of the population to the improved groundnut is 12%. We further find that the awareness of improved varieties is mainly influenced by information access variables, while adoption is largely influenced by economic constraints. The findings are indicative of the relatively large unmet demand for improved groundnut varieties suggesting that there is scope for increasing the adoption rate of improved groundnut varieties in Malawi once the farmers are made aware of the technologies and if other constraints such as lack of access to credit are addressed.

Key words: groundnuts, *adoption, Average Treatment Effect, Malawi*

1 Introduction

The belief that improved technology adoption in driving a Green Revolution has generated enormous interests among researchers and development practitioners to understand the process and barriers to technology change and adoption. Emphasizing on the possibility of a achieving a Green Revolution through technology adoption, Evenson (2003) reports that although it is not widely realized, the 1980s and 1990s were the decades of high productivity growth in crop agriculture most of which came from yield gains resulting from crop genetic improvement, including both the diffusion of existing varieties and the development of new varieties. Three key successes have been reported along the path of achieving a Green Revolution in Africa in the last four decades and they include (i) an increase in the number of new released varieties, (ii) a positive and increasing trend in the rate of adoption of modern varieties, and (iii) while yield increases may not wholly be attributed to varietal improvement, their steady increase in the past four decades provide further evidence that there is potential for further improvement in productivity. Nonetheless, the trends in productivity improvement and food security have uneven across different regions in the world. For example, while hunger and malnutrition has tended to decline in some parts of the world, in Africa, more than one third of the population endures food insecurity which is manifested in the form of under-nourishment and malnutrition (Union Africaine, 2005) and the number of people facing hunger continues to rise each year. Scholarly literature reports on a number of drivers of such a phenomenon in Africa such as the adverse climatic conditions, eg. drought, and other forms of extreme weather that are associated with negative impact on agricultural productivity.

Literature on agricultural technology adoption has focused on, risk, uncertainty (eg Koundouri et al, 2006, and Simtowe et al, 2006), institutional constraints, human capital, input availability imperfect information (e.g Feder et al. 1985; Foster and Rosenzweig 1995), and infrastructure as potential explanations for adoption decisions. However, as reported by Uaeieni et al (2009), a more recent strand of literature focuses on social networks and learning. Explaining the significance of social learning in the adoption process Foster and Rosenzweig (1995) report that farmers may initially not adopt a new technology because of imperfect knowledge about its management; however, adoption eventually occurs due to own experience and neighbors' experience. Consistent with this notion, Conley and Udry (2002) observe that in Ghana, farmer adoption of fertilizer is related to changes in information about the fertilizer productivity of his/her neighbour to the extent that farmers in Ghana used more fertilizer when a neighbour experienced higher than expected profits when they apply more of it. The process of social learning involves awareness creation about an innovation hence it falls with the paradigm of the innovation-diffusion model which states that although an innovation may be technically and culturally appropriate, it may not be adopted due to asymmetric information and high search cost (Uaiene et.al., 2009., Smale et al., 1994).

Related to technology awareness is the perception about the technology by the potential adopter. Adoption literature states that the perceived attributes of the technology condition adoption behaviour of farmers. This means that once exposed to the technology, farmers will gather information about technology attributes which will determine whether or not to adopt it. As reported by Ashby and Sperling (1995) with full information about a technology, farmers may subjectively evaluate the technology differently than scientists. Consistent with this notion, Uaiene et.al (2009), assert that its is thus crucial to understand farmers' perceptions of a given technology in the generation and diffusion of new technologies and farm household information dissemination.

The third strand of adoption literature explains adoption from the point of what Uaiene et.al (2009), call the economic constraint model. Based on this model (see also Shampine, 1998) it is assumed that adoption is conditioned upon the availability of inputs (eg. access to credit, land, labor etc).

Dryland legumes are believed to offer enormous opportunity for reducing food insecurity and poverty in the semi-Arid Tropic especially due to their adoptability to harsh economic conditions and their high likelihood to be adopted by the poor and vulnerable communities. Consequently the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), in collaboration with national partners, has developed and released a number of improved groundnut varieties as away of improving groundnut productivity and competitiveness. In Malawi, varieties released and that are promoted for commercial production include; CG7, ICGV-SM 90704 (Nsinjiro), JL 24 (Kakoma), and IGC 12991 (Baka). The earlier releases include Chalimbana, Chitembana, Mawanga, Manipintar and RG 1. However, the adoption of the improved varieties by smallholder farmers remains low. During the 2004/05-2007/08 period, only 40% of the total harvested groundnut area (260483 ha) was covered by improved groundnut varieties and only 26% of the farmers adopted improved groundnut varieties. The main constraint to the adoption of improved groundnut varieties by farmers has been the lack of access by farmers to sufficient quantity of improved seed. Presently, there is absence of a stable and commercially viable groundnut seed market and hence farmers recycle grain and use as seed. Furthermore, the participation of private traders in the marketing of groundnuts and other grain products following the market liberalization in the 1980s led to the closure of a number of ADMARC selling points that previously acted as major sources of groundnut seed, further aggravating the problem of seed constraints among the farming communities.

In Malawi, although a number of improved groundnut varieties have been released, their *actual* adoption rates by smallholder farmers remains relatively low. Following the release of these improved groundnut varieties they were introduced to farmers through participatory varietal selection (PVS), on-farm research trials and farmer field days. It was anticipated that farmers would have to continue disseminating them through their informal channels, such as the farmer-to-farmer exchange of information, however, a recent study by Simtowe et al. (2009a) reports that the new varieties are only partially known by about 60% of the farming population.

The fact that not all farmers are exposed to the new technologies makes it difficult to obtain consistent estimates of population adoption rates and their determinants using direct sample estimates and classical adoption models such as probit or tobit (see for example Diagne and Demont (2007), Dimara and Skuras (2003), Besley and Case (1993) and Saha et. al., (1994)). The objective of this paper is to assess the actual and potential adoption rates of improved varieties of groundnuts and their determinants using survey data collected from Malawi. We use the Average Treatment Effect (ATE) estimation framework proposed by Diagne and Demont (2007) and use survey data from Malawi to provide estimates of the actual and potential adoption rates of improved varieties of groundnuts and their determinants. Although the study focuses on the diffusion paradigm, we follow Adesina and Zinnah, (1993) and Gemeda et al., 2001) to strengthen the explanatory power of our adoption model by including variables that belong to the category of the perception paradigm as well as those listed under the economic constraint model.

The paper is organized as follows: Section 2 presents a discussion on groundnut production and significance while the ATE framework for estimating adoption rates and their determinants is presented in section 3. Section 4, describes the sampling methodology and the data. The Results and discussions are presented in section 5, while section 6 concludes.

2 Groundnut Significance and production in Malawi

Groundnut is an important legume crop for most parts of the world. Although groundnut originated in South America, it is now widely planted in tropical, sub-tropical and warm temperate areas in Asia, Africa, North and South America, and Oceania (Freeman et al. 1999) and it is the most widely cultivated legume in Malawi. The crop provides a number of benefits to smallholder farmers in developing countries. In Malawi and Senegal, for example, groundnuts account for 25 and 60 percent of household's agricultural income, respectively (Diop et al. 2003). Furthermore, as a legume, groundnut fixes atmospheric nitrogen in soils and thus improves soil fertility and saves fertilizer costs in subsequent crops. This is particularly important when considered in the context of the rising prices for chemical fertilizers which makes it difficult for farmers to purchase them.

Groundnut also forms an important component of both rural and urban diet through its provision of valuable protein, edible oil, fats, energy, minerals, and vitamins. This crop is consumed as such or roasted (more than 32% of supply) or processed into oil (about 52% of supply). In livestock-farming communities, groundnut can be used as a source of livestock feed and increases livestock productivity as the groundnut haulm and seed cake are rich in digestible crude protein content.

In 2005, Malawi ranked 20th in the world groundnut output, producing 161,162 tons valued at US$77.9 million (Nakagawa et al. 1999). Simtowe et al. (2009b) reports that Malawi ranked as the 13th largest producer of groundnut in Africa in the period 2001-2006.. During the period 2001-2006, Malawi produced an annual average of 157 thousand tons of groundnuts per year, which accounted for 2% of the total production in Africa. Within Malawi, groundnut is the most important legume and oilseed crop both in terms of the total area cultivated as well as production). The average annual cultivated area for groundnuts for the period 1991-2006 (171 thousand hectares) accounted for 27% of the total legume land (Simtowe et al. 2009b),

In Malawi, although produced in the entire country, the central and southern Agricultural Development Divisions (ADDs) of Kasungu, Lilongwe, Kasungu, Machinga, and Blantyre accounts for more than 75% of the total area planted to groundnuts. In Kasungu, harvested area for groundnuts was about 22% of the maize area, while in Lilongwe it was about 17% in the year 2008.

With regard to the utilization of groundnuts, more than half the groundnut harvested worldwide is crushed into oil and meal (Freeman et al., 1999). The worldwide groundnut oil production increased from 2.5 million tons in 1961 to 5.6 million tons in 2006 (Simtowe et al 2009b). The groundnut oil share in the total world's oil production declined from 4.8% in the period of 1961-

1989 to 2.9% in the period of 1990-2006, in part, due to a rapid increase in vegetable oil production (FAOSTA 2008). In Malawi, about two thirds of groundnut produced by households is consumed on-farm. The remaining one-third is either sold on the domestics market as raw groundnuts or processed into cooking oil.

3 Empirical Framework

The analysis in this paper is guided by a theoretical framework of technology adoption under partial population exposure proposed by Diagne and Demont (2007). The framework is relevant in this analysis because although a number of groundnut varieties have been released and disseminated in Malawi, a very small fraction of the farming population has been exposed to the technologies. Diagne and Demont (2007) argue that when a technology is new and the target population is not universally exposed to it, the observed sample adoption rate is not a consistent estimator of the true potential population adoption rate. Likewise, classical approaches to the estimation of the determinants of adoption (e.g. probit and tobit models) yield biased and inconsistent estimates even when based on a randomly selected sample..

Diagne and Demont (2007) further argue that this approach is necessary because commonly used estimators of adoption rates suffer from either what is known as “non-exposure” bias or from “selection bias and yield biased and inconsistent estimates of population adoption rates even when based on a randomly selected sample. Consistent with this notion, Besley and Case (1993) Saha et al.(1994), and Dimara and Skura (2003) show that the non-exposure bias also makes it difficult to interpret the coefficients of classical adoption models when the diffusion of the technology in the population is incomplete as the coefficient jointly measure the exposure and adoption. Diagne (2006) shows that the classical full sample adoption rate is a joint estimate of the likelihood of exposure and of the subsequent adoption.

The non-exposure bias results from the fact that farmers who have not been exposed to a new technology cannot adopt it even if they might have done so if they had known about it (Diagne, 2006). This fact leads to the observed sample adoption rate to always underestimate the true population adoption rate when exposure of the population to the new technology is incomplete. The sample adoption rate within the sub sample of farmers exposed to the technology is also not a consistent estimate of the true population adoption rate (even if the sample is random). In fact, the sample adoption rate among the exposed is likely to overestimate the true population adoption rate because of a positive population selection bias by which the subpopulation most likely to adopt gets exposed first. The sources of positive selection bias include farmers' self selection into exposure and the targeting of progressive farmers by researchers and extension workers (Diagne 2006). Selection bias occurs because farmer' exposure to the technology is usually not random. It is likely that national programs and researchers will target technologies at farmers and regions that have a higher propensity to adopt and this leads into a positive population selection bias. Secondly, it is most likely that farmers looking for new technologies will self-select into exposure will be the first to know about the existence of the new technology.

The true population adoption rate corresponds to what is defined in the modern treatment effect literature as the *average treatment effect*, commonly denoted by ATE. The ATE parameter measures the effect or impact of a "treatment" on a person randomly selected in the population (Wooldridge, 2002, chapter 18). In the adoption context "treatment" corresponds to exposure to a technology and the ATE on the adoption outcomes of population members is the population mean adoption outcome. This is the population mean adoption outcome when all members of the population have been exposed to a technology and it is, therefore, a measure of the intrisinc value of the technology as indicated by its potential demand by the population. In that sense, the population mean adoption outcome measured by the ATE parameter is the population mean *potential* adoption. The difference between the population mean potential adoption outcome and the population mean actual (i.e. observed) adoption outcome, which is in fact the combined mean of population exposure to and adoption of the technology, is the population non-exposure bias, also known as the population adoption gap, which exists because of the incomplete diffusion of the technology in the population (Diagne and Demont 2007). Similarly, the mean adoption outcome in the exposed subpopulation corresponds to what is defined in the treatment effect literature as the *average treatment effect on the treated,* (i.e. the mean effect of a treatment in the treated subpopulation), commonly denoted as ATE1 or ATT (Wooldridge, 2002, chapter 18). The difference between the population mean adoption outcome (ATE) and the mean adoption outcome among the exposed (ATE1) is the population selection bias (PSB).The consistent estimation of ATE and ATE1, which are the main focus of the treatment effect methodology, requires controlling appropriately for the exposure status. The details of the estimation procedures of the ATE parameters in the adoption context are given in Diagne and Demont (2007).

The ATE methodology enables the identification and consistent estimation of the population mean adoption outcome $E(y_1)$ and the population mean adoption outcome conditional on a vector of covariates x $E(y_1 \mid x)$, which in this framework corresponds to the *conditional* ATE denoted usually as ATE(*x*) (Wooldridge 2002 chapter 18). One approach to the identification of ATE is based on the so-called conditional independence assumption (Wooldridge 2002, chapter 18) which states that the treatment status w is independent of the potential outcomes y_1 and y_0 conditional on the observed set of covariates z that determine exposure (w). The ATE parameters identified through the conditional independence assumption can be estimated from a random sample of observed $(y_i, w_i, x_i)_{i=1,..,n}$ in three different ways:1) using matching estimators 2) using a weighting estimator and 3) using an estimator based on a parametric regression procedure (see Diagne and Demont 2007 for a detailed discussion on the three estimation methods). In this paper we use the third method, i.e. parametric estimation procedure to estimate the potential population adoption rates and their determinants.

The parametric estimation procedure of ATE is based on the following equation that identifies *ATE*(*x*) and which holds under the conditional independence (CI) assumption (see Diagne and Demont 2007):

$$ATE(x) = \mathrm{E}(y_1 \mid x) = \mathrm{E}(y \mid x, w = 1) \quad \textbf{(1)}$$

The parametric estimation proceeds by first specifying a parametric model for the conditional expectation in the right hand side of the second equality of equation (1) which involves the observed variables *y*, *x* and *w*:

$$E(y \mid x, w = 1) = g(x, \beta) \qquad \textbf{(2)}$$

where g is a known (possibly nonlinear) function of the vector of covariates *x* and the unknown parameter vector *β* which is to be estimated using standard Least Squares (LS) or Maximum Likelihood Estimation (MLE) procedures using the observations (y_i, x_i) from the subsample of exposed farmers only with *y* as the dependent variable and *x* the vector of explanatory variables. With an estimated parameter $\hat{\beta}$, the predicted values $g(x_i, \hat{\beta})$ are computed for all the observations *i* in the sample (including the observations in the non-exposed subsample) and

ATE, ATE1 and ATE0 are estimated by taking the average of the predicted $g(x_i, \hat{\beta})$ *i=1,..,n* across the full sample (for ATE) and respective subsamples (for ATE1 and ATE0):

$$A\hat{T}E = \frac{1}{n}\sum_{i=1}^{n} g(x_i, \hat{\beta}) \qquad \textbf{(3)}$$

$$A\hat{T}E1 = \frac{1}{n_e}\sum_{i=1}^{n} w_i g(x_i, \hat{\beta}) \qquad \textbf{(4)}$$

$$A\hat{T}E0 = \frac{1}{n - n_e}\sum_{i=1}^{n} (1 - w_i) g(x_i, \hat{\beta}) \qquad \textbf{(5)}$$

The effects of the determinants of adoption as measured by the *K* marginal effects of the *K*-dimensional vector of covariates *x* at a given point $\bar{x}$ are estimated as:

$$\frac{\partial E(y_1 \mid \bar{x})}{\partial x_k} = \frac{\partial g(\bar{x}, \hat{\beta})}{\partial x_k} \qquad k = 1,..,K \qquad \textbf{(6)}$$

where x_k is the k^{th} component of *x*.

In our empirical analysis below, we have estimated the ATE, ATE1, ATE0, the population adoption gap ($G\hat{A}P = J\hat{E}A - A\hat{T}E$)[1], and the population selection bias ($P\hat{S}B = AT\hat{E}1 - A\hat{T}E$) parameters using the parametric regression based estimators (equations 3, ,4, and 5).

The estimation of the determinants of exposure is important for its own sake as it can provide valuable information regarding the factors influencing farmers' exposure to a new technology. These factors, which are mostly related to the diffusion of information, can very well be different from those influencing the adoption of the technology once exposed to it. In our estimation of the parametric regression based estimators, since *y* is a binary variable in our empirical analysis, the equation 2 above is effectively a parametric probabilistic model. We therefore have $E(y \mid x, w = 1) = P(y = 1 \mid x, w = 1)$ with an assumption of a probit model, $g(x, \beta) = \Phi(x\beta)$. In this case the parametric estimation of ATE reduces to a standard probit estimation restricted to the exposed sub-sample. The marginal effects in equation (6) are also

[1] Note that as discussed earlier, the joint exposure and adoption parameter (JEA) is consistently estimated by the sample average of the *observed* adoption outcome values: $J\hat{E}A = \frac{1}{n}\sum_{i=1}^{n} y_i$.

estimated using this ATE parametric model. For comparison purposes, we have also estimated a "classic" probit adoption mode which is a model of the determinants of joint exposure and adoption. The estimation was done in STATA using the Stata *add-on adoption* command developed by Diagne (2007) to automate the estimation of ATE adoption models and related statistical inference procedures (see Diagne, 2008). In the empirical estimation we also test the effect of a number of other factors reported in literature regarding the effect technology adoption. For example, Feder and Umali (1993) and Cornejo and McBrid (2002) review factors that affect technology adoption and report that technology adoption is linked to resource endowment in terms of human, physical and financial capital as well as the characteristics of the technology itself. Conley and Udry (2003) cited in Phillips 2008 show that farmers adjust their activities in line with the successful experimentation of others, such that social networks are important for information sharing and consequently for adoption to occur. Related to the issue of information sharing, there is considerable literature discussing the role of formal and informal information sources in facilitating technology diffusion and adoption. We include such factors in our analysis in which we explore factors that affect technology awareness and those that affect technology adoption. While we expect some factors to have a similar effect on both, some factors that affect awareness of the technology by the farmer may be different from those that affect the decision to adopt.

4. Data

The data used in this analysis were collected by the International Crops Research Institute for the semi-Arid Tropics (ICRISAT), in collaboration with the Centre for Agricultural Research and Development (CARD) of the University of Malawi and the National Smallholder Farmer's Association (NASFAM) in between April and May 2008, in Malawi. The data were collected through a household survey conducted in the four districts of Chiradzulu, Thyolo, and Balaka and Mchinji. A multi stage sampling procedure was employed in selecting households for the survey. The first stage involved a purposeful sampling of the four districts where groundnuts are grown. Once the districts were selected, the second stage involved a purposeful selection of four largest groundnut producing sections[2] in each district. Consequently this led to the selection of 16 sections for the study area. Third, a complete list of all the villages in each section was drawn with the help of the heads of Extension Planning areas (EPA) and their staff. Three (3)

[2] Malawi is divided into eight ADDS that form different ago-ewlogical zones. These ADDS lie within the three regions of the country. The ADDs constitute the primary management unit of extension services. The ADDs are subdivided into Rural Development Projects (RDPs), which are further subdivided into Extension Planning Areas (EPAs). The EPAs are further sub-devided into sections Extension agents called Field Assistants supervise at the section level

villages were randomly selected from each section. Fourth, and last a complete list of all farm families was then drawn for each of the randomly sampled villages. Thirteen (13) farmers were randomly sampled from a list of farm families in each village. This led to the selection of 594 households for the household survey. Data were collected at village and at farm-household levels. At the village level, data collected included crops grown, prices offered for crop produce, and the village infrastructures. At the farmer level data collected included the farmer knowledge of varieties and varieties cultivated in 2006/07. Prior to the survey a list of known modern and traditional varieties in the village was constructed and each farmer selected for the survey was asked whether he or she knew each of the varieties and crops. If the answer to the question was a 'yes' then the farmer was asked whether he or she had ever cultivated the variety and if he or she cultivated it in 2006/07 season. In the present study we define knowledge or exposure to a variety as a "yes" answer to the first question and adoption as the cultivation of the variety. The farm level survey also collected valuable information on several factors including household composition and characteristics, land and non-land farm assets, livestock ownership, household membership in different rural institutions, costs of production, yield data for different crop types, indicators of access to infrastructure, household market participation, household income sources and major consumption expenses.

Farm household characteristics

Table 1 reports descriptive statistics disaggregated by their adoption status for 440 surveyed farmers. Adopters are defined as households that planted at least one variety of improved groundnuts during the 2006/07 cropping season. Improved groundnut varieties were grown by 25% of the sampled households in 2006/07 cropping season. About three-quarters of the households were male-headed and there were no significant differences in the distribution of the gender of household head between adopters and non-adopters. The average age of the household is about 45 years and there are no significant differences in ages between the adopters of improved groundnuts and those that did not. The household size for the sampled households is 5 persons per household. This is slightly higher than the national average of 4.4 persons per household (National Statistics Office, 2005) and the differences in age between adopters and non-adopters is not significant. The average land holding size for the sampled households is 2.5 acres (equivalent to 1 hectare) and adopting households have significantly larger holding of land (3.3 acres) than the non-adopting households (2.3 acres). The education level of the household's head is expressed in terms of years of schooling results indicate that the average number of years of education for the head of households in the sample is 4.8yrs. Adopting households have significantly more years of education (5.2yrs) than non-adopting households (4.7yrs) suggesting that there is a positive correlation between adoption and the number of years of formal education. The average number of years of experience in groundnut farming is 9.4 years. Adopting households have significantly more years of experience in groundnut farming (12.8) than non-adopters (8.2 yrs). It is further observed that farmers that grew improved groundnut varieties also have more years of experience in the cultivation of groundnuts. There are also wide differences in market access between adopting households and those that did not. For example, the proportion of farmers reporting that they received credit[3] (formal and informal) in 2006/07 is significantly higher among adopters (25%) than non-adopter (12%) which is indicative of the positive correlation between the adoption of improved groundnuts varieties and access to liquidity. The average distance to the village market for the sample households is 1.9 km. Adopting households have significantly shorter distances to the village market (1.3km) than non adopting households (2.1km). The findings suggest that farmers with access to markets have a higher propensity to adopt improved groundnut varieties than those that with limited access to markets. Other than accessing information and seed through markets, farmers may also access information about improved varieties through social groupings such as farmer's clubs whose primary aim is to promote agricultural technology adoption as well as other social groupings whose primary objective is not necessarily linked to agriculture. Such groupings facilitate the informal exchange of information among farmers. Results indicate that about 8% of the farmers are members of farmer clubs. However, a significantly larger proportion of adopters (11%) are members of farmer's clubs against 7% for non-adopters. Membership in religious and other social groupings was reported by 12.5% of the farmers and a significantly larger proportion of non-adopting farmers are members of faith based organization against only 1% for the adopting households. It is also observed that adopting households have a significantly high amount of household off-farm income (MK28,500) against MK 16977 for non-adopting households.

[3] In this study access to credit combines both formal credit from the bank or microfinance institution and credit from informal sources such as friends and relatives

Table 1: Household characteristics by adoption status of improved groundnuts in 2006/07

Characteristic	Non-adopters (n=442) 75%	Adopters (n=152) 25%	Total (n=594)	Difference
Socio-demographic factors				
Proportion of male farmers	75.5 (2.0)	77.6.(3.3)	76.1(1.7)	-2.0(4.0)
Age	45.3 (0.85)	43.1 (1.2)	44.7 (0.7)	2.1 (1.6)
Household size	4.9 (0.17)	5.1 (0.28)	5.0 (0.15)	-0.17(0.3)
Years of residence in the village	30 (0.9)	30(1.4)	30.1(0.77)	0.06(1.8)
Land holding size	2.3 (0.08)	3.3 (0.16)	2.5 (0.07)	-1.1 (0.16)***
Off-farm income (MK)	16977 (1999)	28500(8568)	19912(2645)	-11523(6059)*
Value of assets (MK)	6021 (639)	8306 (1665)	6606 (639)	-2285 (1463)
Education and experience farming				
Years of schooling	4.7 (0.10)	5.2 (0.16)	4.8 (0.08)	-0.5(0.19)***
Years of experience in pigeonpea farming	14.0 (0.72)	14.9 (1.4)	14.2 (0.64)	-0.87(1.6)*
Years of experience in groundnut farming	8.2 (0.56)	12.8 (1.0)	9.4 (0.49)	-4.1(1.13)***
Institutional factors				
Proportion farmers with access to credit	12 (2)	25 (4)	15.6 (1.4)	-12 (3)***
Distance to village market	2.1 (0.11)	1.3 (0.22)	1.9 (0.1)	0.77 (0.23)***
Distance to the farmer club	0.39 (0.07)	0.86(0.21)	0.51(0.07)	-0.47 (0.18)***
Distance to an agricultural office	4.7(0.13)	5.3(0.27)	4.8(0.12)	-0.6 (0.27)**
Contacts with government extension	5.5 (0.89)	6.1(1.5)	5.6 (0.77)	-0.52 (1.77)
Contacts with NGO extension worker	1.2 (0.61)	1.42 (0.66)	1.3(0.48)	-0.22 (1.1)
Membership in faith based organization (%)	30.1 (9)	0.50 (0.14)	12.5 (1.3)	12.5 (2.7)***
Membership in a farmer's club (%)	6.7(1.1)	11.1(2.5)	7.9(1.1)	-4.3(2.5)*

Source: ICRISAT Treasure Legumes/ TLII Study (April- May 2008)

* Indicate that difference between adopters and non-adopters is statistically significant at 95% level (t-tests are used for differences in means)

5.0 Results and Discussions

5.1 Patterns of improved groundnut diffusion and aAdoption

In this study, respondents were asked to provided information about the crop varieties that they knew. As reported in Table 2, 60% of the respondents are aware of at least one improved variety of groundnuts (CG7, chalimbana 25, manipintar, baka and nsinjiro). Knowledge of improved groundnuts varieties is more prevalent in Mchinji (81%), Balaka (76%) and Thyolo (62%) than Chiradzulu where only 20% of the farmers expressed awareness of improved groundnut varieties.

Among the improved varieties, CG7 is the most widely known (53%) while the second most widely known improved variety is Chalimbana 2005, known only by 11% of the farmers. There is an opportunity for ICRISAT to use existing structures for government extension services to disseminate the information to farmers in potential groundnut growing areas.

Although more respondents expressed awareness of the improved varieties, fewer reported ever growing them and a much smaller proportion of them actually grew them in 2006/2007 season. Although 60% of the farmers expressed some knowledge of the crop, only 25% reported that they grew at least one improved variety in the 2006/2007 season. CG7 is the most widely cultivated variety grown my 26% of the respondents. However, these sample adoption may not provide a reliable estimate of the population adoption rates due to the non-random nature in which farmers get exposed to the varieties. Therefore, these sample adoption rates are likely to be biased downwards because they include farmers who were not yet exposed to the varieties and therefore they can not adopt unless exposed. In fact some farmers would have adopted the improved groundnut varieties if they had been exposed to them, but in this sample adoption rates they are considered as non adopters. Therefore, an assessment of adoption rates among the exposed sub-population appears more appealing in terms explaining the potential adoption rates because it some how addresses the problem of non-exposure bias.

As indicated in Table 2, the adoption rate among the sub-sample of farmers that were aware of improved groundnut is much higher than the adoption rates reported earlier for the whole sample. The overall adoption rate for at least one improved groundnut variety among the sub-sample of exposed farmers in 2006/07 season is 43% compared to a lower adoption rate of 26% for the whole sample.

Table 2: Diffusion and adoption of groundnuts: Proportion of farmers that are aware and those that adopted in 2006/2007

Characteristic	Chiradzulu	Thyolo	Balaka	Mchinji	Total
Know the variety (%)					
CG 7	14	57	73	68	53
Chalimbana	81	81	97	79	84
Manipintar	22	5	6	11	11
Chalimbana 2005	3	5	1	28	9
Kalisere	0	0	1	18	5
ICGV-90704 (Nsinjiro)	3	1	6	3	3
ICG 12991 (Baka)	0	0	12	1	3
JL 24 (Kakoma)	1	1	3	3	2
Know at least one improved variety	20	62	76	81	60
Ever planted (%)				!	
CG 7	9	45	41	56	88
Chalimbana	65	60	80	71	69
Manipintar	20	3	3	9	9
Chalimbana 2005	2	5	1	25	8
Kalisere	0	1	1	18	5
ICGV-90704 (Nsinjiro)	3	0	4	3	3
ICG 12991 (Baka)	0	0	6	0	2
JL 24 (Kakoma)	0	1	1	3	1
Planted in 2006/07 season (%)					
CG 7	7	36	29	33	26
Chalimbana	42	44	62	48	49
Manipintar	11	2	0	7	6
Chalimbana 2005	3	3	1	21	8
Kalisere	0	0	1	10	3
ICGV-90704 (Nsinjiro)	2	0	3	2	2
ICG 12991 (Baka)	0	0	2	0	1
JL 24 (Kakoma)	0	1	1	1	1
Planted at least one improved variety	4.6	20.8	32.6	44.2	26
Planted in 2006/07 season (% of the exposed sub-sample)					
Planted at least one improved groundnut variety	22.6	33.7	42.7	54.4	42.8

Source: ICRISAT Treasure Legumes/ TLII Study (April- May 2008)

The adoption rates are generally higher in Mchinji district compared to the other districts. While adoption rates for the exposed sample seem more plausible in explaining potential population adoption rates, Diagne (2006) reports that they are likely to significantly over-estimate the population adoption rate due to the positive population selection bias by which the population most likely to adopt gets exposed first. Diagne (2006) points out that the positive selection bias arises from two sources. The first source is the farmer's self selection into exposure. The second source of selection bias is the fact that researchers and extension workers target their technologies at farmers that are more likely to adopt.

5.2 Determinants of exposure to improved groundnut varieties

In this study, about 60% of the sample households were exposed to a t least one of the improved groundnut varieties (CG7, Chalimbana 2005, ICGV-90704 (Nsinjiro), ICGV 99568 (Chitala), ICG 12991 (Baka) and JL 24 (Kakoma). Based on this information, we estimate a probit regression of factors that affect the propensity of exposure to improved varieties of groudnuts. Table 4 depicts results from a probit estimation of the determinants of the probability of getting exposed to at least one improved groundnut varieties. Several variables show statistically significant coefficients at 5% level. The coefficient for education is positive and statistically significant at 1% suggesting that more years of education increase the propensity of and individual to get exposed to improved groundnut varieties. .

The membership in a social grouping such as a faith based organization has a positive and significant effect on the propensity to get exposed to improved varieties. This finding is also consistent with the debate on the role of social interactions in determining the rate at which technologies are adopted (see for example, Conley and Udry 2005, Manski., 2004). While the activities in such groups are not primarily social interactions they shape local social norms and networks that stimulate information sharing and social learning, a process that has a bearing on technology awareness. Acknowledging the role of social interactions in technology diffusion, Rogers (1995) contends that the diffusion process consists of interpersonal network exchanges between those individuals who have already adopted an innovation and those who are then influenced to do so. Such a process can be enhanced by farmer' membership in social grouping that also strengthens their social capital. The number of years of residence in a village has a positive and significant effect on the propensity to get exposed to improved varieties which again provides evidence of the significance of social capital in information sharing

The coefficient for the number of years of experience in groundnut farming is positive and significant at 5% level suggesting that farmers with prior experience in growing of groundnut have a higher propensity to get exposed to new varieties. This may be attributed to framers own effort to look for new varieties due his previous interests and experience in the crop, or it might be attributed to other factors that enable groundnut farmers to get networked to information on the existence of improved varieties.

The proxy variables for access to agricultural extension (e.g distance to an agricultural office and membership in a farmers club) where information on improved varieties is shared returned insignificant but expected coefficients. The findings highlight the declining role of government as source of variety information or as a provider of extension services, particularly for groundnuts. This is apparently attributed to the fact that in the early 1980s, Malawi pursued a structural adjustment path which entailed allowing the private sector to participate in input and out marketing of smallholder produce and the restructuring of the government extension system. As reported by Kumwenda and Madola (2005), the reform process also required government to undertake cutbacks in expenditure including funding to the Ministry of Agriculture hence it greatly affected the government provision of extension services. Furthermore, the formal government extension system is biased towards maize, the main staple and tobacco, the main cash crop while legumes such as groundnuts do not feature highly in the system.

The variable capturing access to markets (the distance to the nearest main market) returned a negative and expected sign, but it was not significant.

The coefficients for gender of the household head, contact with NGO extension workers, were not significant. District dummy variables of Mchinji, Balaka and Thyolo, returned positive and significant coefficients indicating that farmers that resided in the three districts had a higher propensity to get exposed to at least one improved groundnut varieties compared to those in Chiradzulu.

Table 3: Determinants of the of probability of exposure to improved groundnuts

Variables	Coefficients		Marginal effects	
	Coeff	SE	Coeff	SE
Gender of head (1=Male, 0=Otherwise)	-0.0131	0.1564	-0.0050	0.0599
Age of head (yrs)	-0.0051	0.0046	-0.0020	0.0018
Education of head (yrs)	0.0553***	0.0182	0.0212***	0.0070
Household size	0.0396	0.0288	0.0152	0.0111
Distance to the main market	-0.0080	0.0139	-0.0030	0.0053
Distance to an agricultural office	-0.0279	0.0202	-0.0107	0.0077
Membership is a social/Christian/faith based group (1=yes, 0= otherwise)	0.3276*	0.1876	0.1200*	0.0649
Membership in farmer club (1=yes, 0= otherwise)	0.2508	0.2320	0.0927	0.0819
Membership in producer marketing group (1=yes, 0= Otherwise)	0.0257	0.3835	0.0098	0.1460
Number of years lived in village	0.0100**	0.0043	0.0038**	0.0017
Number of contacts with NGO extension officers	0.0001	0.0057	0.0000	0.0022
Years of experience in groundnut farming	0.0072	0.0061	0.0028	0.0023
Ownership of a radio	0.0715	0.1283	0.0274	0.0493
Mchinji	1.9154***	0.1930	0.5402***	0.0364
Balaka	1.7454***	0.1828	0.5024***	0.0366
Thyolo	1.1379***	0.1651	0.3716***	0.0441
Constant	-1.4168***	0.3281		
Number of interviews	594			
Pseudo R2	0.222			
LR Chi ^{2}	177.71			

Source: ICRISAT Treasure Legumes/ TLII Study (April- May 2008)
Key : * p<0.10; ** p<0.05; *** p<0.01

5.3 Adoption rates for improved Groundnuts and their Determinants

5.3.1 Adoption rates for improved groundnuts

The adoption estimates for improved groundnuts are presented in Table 4. The results show that the sample adoption rates – (joint exposure and adoption rate) is the same for the ATE probit, and the classic probit estimated at 26% and that they all yield the same range for the 95% confidence interval (between 22 % and 29 %). Again the finding that the sample estimate is the same as the estimate obtained by ATE probit method suggests that the assumptions underlying the models (eg, random sampling, distribution) are plausible in as far as estimating the joint exposure and adoption rate for the whole population and its determinants is concerned (Diagne and Demont, 2007).

The joint exposure and adoption rate within the subpopulation that is exposed to the improved groundnut varieties estimated by the classical probit model (33%) is different from those estimated by the sample moments and ATE-probit model (43%). Indeed it can be seen that the classic probit model estimate of 33% has a 95% confidence interval ranging between 30% and 35%, a range that is far below the consistently estimated value of 43%, a finding that suggests that the classic probit model has a problem of attenuation bias (Yatchew and Griliches, 1985) because the model is based on the full sample without controlling for exposure bias. Diagne and Demont (2007) note that the downward bias of the classical probit model estimate of the probability of joint exposure and adoption for the exposed subpopulation implies that its coefficient estimates are likely to be inconsistent for a model of determinants of adoption. These results, therefore, represent the expected joint exposure and adoption rate for the population which is not the desirable parameter of interest in most adoption studies.

The desirable parameter in adoption studies is the full population adoption rate (ATE) which provides an estimate of the potential demand of the groundnut technology by the target population. The full population adoption rate for improved groundnut is estimated to be 37% for ATE probit method. This implies that the improved groundnut adoption rate in Malawi could have been 37% in 2007 if the whole population had been exposed to improved varieties of groundnut, instead of the joint exposure and adoption rate of 26%. Thus when compared to the current sample adoption rate of 26%, there is a substantial population adoption gap of 12% due to the population's incomplete exposure to the improved groundnut varieties. The estimated adoption gap is statistically significantly different from zero at 1% level. This finding implies that there is potential for increasing the adoption rate by 12% once all farmers become aware of at least one improved groundnut variety.

Table 4: Estimates of improved groundnuts adoption rates and their 95% confidence intervals [a] among all farmers

Parameters	Sample moments estimate	Classical probit joint exposure and adoption model	ATE probit adoption model
Joint exposure and adoption rate (Probability of knowledge and adoption of at least one improved groundnut variety):			
In the full population	0.26(0.22- 0.29)	0.26 (0.22- 0.29)	0.26 (0.22- 0.29)***
Within the improved groundnut -exposed subpopulation	0.43 (0.29- 0.48)	0.33 (0.30- 0.35)	0.43 (0.38- 0.47)***
Groundnut adoption rate (Probability of adopting at least one improved groundnut):			
In the full population (ATE)			0.37 (0.32 0.42)***
Within the improved groundnut – exposed subpopulation (ATE1)			0.43 (0.38- 0.47)***
Within the sub-population not exposed to the improved groundnut (ATE0)			0.29 (0.23 0.28)***
Estimated population adoption gap:			
Expected non-exposure bias(NEB)			-0.12(-0.14 -.09)***
Expected population selection bias (PSB)			0.05 (0.03 -.08)*

Source: ICRISAT Treasure Legumes/ TLII Study (April- May 2008)

Key : * p<0.10; ** p<0.05; *** p<0.01

The adoption rate within a sub-population of farmers that are exposed to at least one improved groundnut variety (ATE1) is estimated to be 43% for the ATE parametric probit model, while the estimated potential adoption rate within the sub-population not yet exposed to groundnut variety (ATE0) is 29% for the parametric probit model. The estimated population selection bias which is measured by the difference in the potential adoption rate between the exposed sub-population (43%) and the consistently estimated population adoption rate (37%) is estimated at 5% and it is statistically significant from zero. This positive populations selection bias implies that the adoption probability for a farmer belonging to the sub-population of informed farmers is significantly higher than the adoption probability for any farmer within the population. Consequently, we reject the null hypothesis that a farmer selected randomly within a population has the same probability of adopting improved groundnut varieties as a farmer selected within the sub-population of those informed about improved groundnut varieties.

The above adoption rates are based on full sample of farmers that included three groups; thus, (i) non-groundnut growers, (ii) groundnut growers that did not adopt improved varieties, and (iii) groundnut growers that adopted improved varieties. Therefore the results on potential adoption rates measure the adoption probability of improved groundnut varieties by a farmer randomly selected for a population composed of the three groups described above.

However, we out of curiosity also examine the potential adoption rate of improved groundnut varieties among a sub-population of farmers that grew groundnut, thus excluding farmers that did not grow any groundnut variety. As depicted in Table 5, the adoption rate of improved groundnuts within a sub-sample of farmers that grew groundnuts in 2006/07 is estimated to be 46% and this is significantly higher than the 26% sample adoption rate of improved groundnut varieties for the whole sample that was presented in Table 4. The consistently estimated potential adoption rate for improved groundnut varieties within a sub-population of groundnut growers is 58% and this is higher than the 37% potential adoption rate reported for the whole population of farmers that includes non-groundnut growers. The adoption gap resulting from non-exposure to improved varieties by groundnut growers is estimated at 11% and significant at 1% level, suggesting that if all currently groundnut growers were exposed to improved groundnut varieties, the adoption rate would increase from 46% to 58%. Apparently, this also implies that there is slightly lower potential for increasing the adoption rate of improved varieties among the already groundnut-growing sub-population than there is for the whole population farmers whose adoption gap is estimated to be 12 %.

Table 5: Estimates of improved groundnuts adoption rates and their 95% confidence intervals [a] among groundnut growing households

Parameters	Sample moments estimate	Classical probit joint exposure and adoption model	ATE probit adoption model
Joint exposure and adoption rate (Probability of knowledge and adoption of at least one improved groundnut variety):			
In the full population	0.46(0.40- 0.51)	0.46 (0.21- 0.26)	0.46 (0.41- 0.50)***
Within the improved groundnut-exposed subpopulation	0.60(0.53- 0.85)	0.40 (0.36- 0.42)	0.60 (0.53- 0.68)***
Groundnut adoption rate (Probability of adopting at least one improved groundnut):			
In the full population (ATE)			0.58 (0.52 0.64)***
Within the improved groundnut – exposed subpopulation (ATE1)			0.61 (0.55- 0.66)***
Within the sub-population not exposed to the improved groundnut (ATE0)			0.52 (0.42- 0.61)***
Estimated population adoption gap:			
Expected non-exposure bias(NEB)			-0.13(-0.15 -.11)***
Expected population selection bias (PSB)			0.02 (0.00 -.04)

Source: ICRISAT Treasure Legumes/ TLII Study (April- May 2008)

Key : * p<0.10; ** p<0.05; *** p<0.01

5.4 Determinants of adoption of improved groundnut varieties

Results on the determinants of improved groundnut adoption for the classic "adoption" model, and ATE probit model are presented in Tables 6. There are striking differences in the magnitude of the coefficients as well as their marginal effects between the two models. In general the marginal effects of the ATE probit model are larger in absolute values than those of the classic "adoption" model. The observed findings are consistent with the theoretical expectation in that as reported by Diagne and Demont (2007), the conditional mean "adoption" function estimated in the classical adoption model is equal to the true population average conditional adoption function (the "true" population adoption function) multiplied by the probability of being aware of the technology. Hence, for a factor determining adoption alone and not awareness, its marginal effect calculated from the classical "adoption" model is equal to its marginal effect from the true adoption model multiplied by the conditional probability of awareness, a quantity always between 0 and 1 and usually very small when not many farmers are aware of the technology. It is also important to note that some coefficients are significant in both models while some are significant only in the ATE probit model. Results show that factors such as the age of the of the head of household, the age of a farmer, the land holding size, access to credit, number of years of residence in a village, membership in a producer marketing group and ownership of radio, among others, has a significant effect on the adoption of improved groundnut varieties.

Table 6: Determinants of adoption of improved groundnuts- Estimated coefficients

Variables	ATE adoption		Classic adoption	
	Coef	SE	Coef	SE
Gender of head (1=Male, 0=Otherwise)	-0.0927	0.2035	-0.1521	0.1716
Age of head (yrs)	-0.0130**	0.0066	-0.0131**	0.0055
Education of head (yrs)	-0.0118	0.0233	0.0094	0.0197
Household size	0.0321	0.0358	0.0196	0.0312
Land holding size (acres)	0.0713*	0.0429	0.0949**	0.0389
Access to credit(1=yes, 0=otherwise)	0.6118***	0.1870	0.6616***	0.1612
Distance to the main market (km)	0.0279*	0.0163	0.0173	0.0141
Distance to an ag.ric office	0.0516**	0.0248	0.0202	0.0214
Membership in farmer club (1=yes, 0= otherwise)	0.1514	0.2851	0.2054	0.2616
Number of years lived in village	-0.0059	0.0058	-0.0003	0.0050
Contact with NGO extension worker (1=yes, 0=otherwise)	0.0112	0.0102	0.0031	0.0037
Number of years of experience in groundnut farming	0.0295***	0.0090	0.0213***	0.0068
Amount of non-farm income (MK)	0.0000	0.0000	0.0000	0.0000
The value of assets (MK)	0.0000	0.0000	0.0000	0.0000
Livestock ownership (1-yes, 0=otherwise)	0.0000	0.0000	0.0000	0.0000
Proportion of land allocated to tobacco (%)	-0.0149*	0.0084	-0.0205**	0.0081
Membership is a social/faith based group (1=yes,0= otherwise)	-0.4771	0.2916	0.4884	0.3549
Membership in a producer marketing group (1=yes,0= otherwise)	0.8921*	0.4916	-0.3226	0.2386
Ownership of radio (1=yes,0= otherwise)	0.3564**	0.1615	0.2968**	0.1451
Mchinji	0.6166**	0.2996	1.5951***	0.2555
Balaka	0.3608	0.2851	1.2005***	0.2288
Thyolo	0.0872	0.2936	0.7910***	0.2274
Constant	-1.0898**	0.4660	-2.1004***	0.4016
Number of interviews	594		594	
Pseudo R2				
LR Chi 2				
AIC				

Source: ICRISAT Treasure Legumes/ TLII Study (April- May 2008)

Key : * p<0.10; ** p<0.05; *** p<0.01

The coefficient for age of the head of household is negative and significant at 5% suggesting that the probability of adopting at least one improved groundnut variety diminishes with old age. Adoption literature largely shows that the impact of the age of a farmer on adoption is can not be pre-determined because older farmers are sometimes considered to be risk-averse and thus less willing to try new innovations than younger farmers. The other strand of literature considers older farmers as experience and therefore in a better position to make sound judgment regarding the adoption of new technologies, suggesting that older farmers will be quick to adopt improved technologies that offer better returns than younger and inexperience farmers. Therefore, the negative effect of age on adoption can also be interpreted in terms of the risk-aversion paradigm assuming that farmers consider the new technologies to be riskier than older technologies that they have been growing for a long period of time. However, one other possible explanation for the negative coefficient can be drawn from the innovation diffusion paradigm which largely assumes that technology is technically and culturally appropriate but the problem of adoption is one of asymmetric information and very high search costs (Feder and Slade, 1984). Therefore, older farmers may incur higher search costs for the new technologies, hence lack information on their existence and hence fail to adopt them

A number of wealth related variables returned significant and expected coefficients. The size of the land owned by the household returned a positive and significant coefficient suggesting that farmers with larger holdings are more likely to adopt improved varieties than younger farmers. Also consistent with the economic constraint paradigm of adoption models, we find that access to credit returned an expected positive and significant coefficient, suggesting that agricultural credit in Malawi can have a significant impact in facilitating the adoption of improved groundnut varieties. This implies that there exists a great scope for increasing the cultivation of improved groundnut through an improved access of farmers to credit markets which may enable them to purchase seed and other related inputs.

The ownership of a radio returned a positive and significant coefficient suggesting that households that own radios have a higher propensity to adopt improved varieties of groundnuts than those that do not own a radio. The ownership of a radio may enhance technology adoption through improved access to information about new varieties released and seed sources, however it may also be an indicator of a wealthier household that has the equity required to purchase related inputs such as seed. In this study, since the ownership of the radio had no effect on the status of farmer's awareness of the improved varieties, this may suggest that the ownership of a radio is merely a wealth indicator variable which proxies the household's ability to acquire inputs required for the adoption of improved groundnut varieties.

In general the significance of wealth related variables may alos e explained by the economic constrain paradigm of adoption models which states that input fixity in the short run, such as access to credit, land, labor or other critical inputs limits production flexibility and conditions technology adoption decisions (Uaiene et al. 2009). One constraint to groundnut cultivation is the lack of seed. The positive coefficient for most of the wealth related variable may therefore be explained by the fact that economically well-off farmers have the necessary equity acquire seed and other complementary inputs than poorer farmers.

The number of years of experience in groundnut farming returned a positive and significant coefficient. This is consistent with prior expectation as experience farmers in groundnut farming are more likely to have a sound knowledge about the intrinsic benefits of a new technology which they could the use for judging whether or not to adopt the technology.

The membership in a producer marketing group returned a positive and significant coefficient indicating that although farmers that are member of such groupings have a higher propensity to adopt improved varieties. Being resident in Mchinji district increases one's propensity to adopt improved groundnut varieties, a finding that is consistent with expectation as Mchinji is the major groundnut growing district for Malawi. As a matter of fact, groundnut is a major cash crop for farmers in Mchinji, hence they tend to intensify its production and thus would be more willing to intensify production through investment in improved technologies.

Variables capturing access to markets such as distance to the village market and distance to the agricultural extension office retuned significant but unexpected signs of coefficient. The results indicate that contrary to prior expectation, adoption is more likely to occur among households that are further away from the market and further away from the extension service providers. The intuition drawn from such findings is that formal ways of promoting the adoption of technology such as through a government extension system have become irrelevant in the promotion of groundnut production.

6. Conclusions

This paper has provided estimates of actual and potential adoption rates and the determinants of adoption for the improved groundnut varieties in Malawi and has shown the importance of appropriately controlling for exposure and selection bias when assessing the adoption rates of a technology and its determinants. The study has shown the importance of appropriately controlling for exposure and selection bias when assessing the adoption rates of a technology and its determinants. We find that improved groundnut adoption rates in Malawi could have been up to 37% in 2007 instead of the observed sample adoption rate of 26% if the whole population was exposed to the improved groundnut varieties by the year 2007. The non-exposure bias of 12% suggests that there is potential for increasing the adoption rate of improved groundnut by 12% if its diffusion to the population can be completed.

About 60% of the sampled households expressed awareness of the improved varieties of groundnuts. While most of the information on improved groundnuts appears to be disseminated through Informal mena such as farmer- to- farmer exchange of information, there is a huge potential of using existing formal institutions and methods in the dissemination of information on improved groundnut. The formal methods that have proven to be effective are already in place and they include on-farm trials, demonstration plots controlled by agricultural extension agents, field days for farmers, and agricultural shows to which farmers are invited.

Furthermore, the study has shown that the exposure to improved groundnut varieties and their adoption by farmers is influenced by a number of other factors and that in some cases , factors affecting the two outcome (exposure and adoption) are different. The probability of a farmer's awareness of at least one improved groundnut variety is higher among farmers with more years of education, among farmers that are members of faith based organization and those that have lived longer in the village of residence at the time of the survey.

Signifying the presence of economics constraints, the study has shown that the propensity of cultivating (adopting) at least one improved groundnut variety is high among farmers that have access to credit services as well as among wealthier farmers. These findings point to the importance of improving farmers access to financial markets that enable them to acquire credit to purchase seed for improved groundnut. The policy implication is that supporting farmers, with credit and extension services would significantly increase their participation in the cultivation of improved groundnut varieties.

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Appendix 1: Determinants of adoption of improved groundnuts-Marginal effects

Variables	Dy/dx adoption ATE adoption		dy/dx classic probit	
	Coef	SE	Coef	SE
Gender of head (1=Male, 0=Otherwise)	-0.0346	0.0765	-0.0427	0.0496
Age of head (yrs)	-0.0048**	0.0024	-0.0036**	0.0015
Education of head (yrs)	-0.0044	0.0086	0.0026	0.0053
Household size	0.0118	0.0132	0.0053	0.0085
Land holding size (acres)	0.0264*	0.0158	0.0258**	0.0106
Access to credit(1=yes, 0=otherwise)	0.2359***	0.0727	0.2094***	0.0565
Distance to the main market (km)	0.0103*	0.0060	0.0047	0.0039
Distance to an ag.ric office	0.0191**	0.0092	0.0055	0.0058
Membership in farmer club (1=yes, 0= otherwise)	0.0572	0.1098	0.0599	0.0817
Number of years lived in village	-0.0022	0.0021	-0.0001	0.0013
Contact with NGO extension worker (1=yes, 0=otherwise)	0.0041	0.0038	0.0008	0.0010
Number of years of experience in groundnut farming	0.0109***	0.0033	0.0058***	0.0018
Amount of non-farm income (MK)	0.0000	0.0000	0.0000	0.0000
The value of assets (MK)	0.0000	0.0000	0.0000	0.0000
Livestock ownership (1-yes, 0=otherwise)	0.0000	0.0000	0.0000	0.0000
Proportion of land allocated to tobacco (%)	-0.0055*	0.0031	-0.0056**	0.0022
Membership is a social/faith based group (1=yes,0= otherwise)	-0.1607*	0.0877	0.1574	0.1296
Membership in a producer marketing group (1=yes,0= otherwise)	0.3443***	0.1749	-0.0782	0.0513
Ownership of radio (1=yes,0= otherwise)	0.1305**	0.0580	0.0800**	0.0386
Mchinji	0.2354**	0.1132	0.5212**	0.0796
Balaka	0.1370	0.1088	0.3916***	0.0768
Thyolo	0.0325	0.1099	0.2483***	0.0764

Source: ICRISAT Treasure Legumes/ TLII Study (April- May 2008)

Key : * $p<0.10$; ** $p<0.05$; *** $p<0.01$