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Welfare Effects of Agricultural Technology adoption: the case of improved groundnut varieties in rural Malawi

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Abstract

This paper applies a program evaluation technique to assess the causal effect of the adoption of improved groundnut technologies on consumption expenditure and poverty measured by headcount, poverty gap and poverty severity indices. The paper is based on a cross-sectional farm household level data collected in 2008 from a sample of 594 households in rural Malawi. A sensitivity analysis is conducted to test the robustness of the propensity score based results using the rbounds test and the mean absolute standardized bias (MASB) between adopters and non-adopters. The analysis reveals robust and positive and significant impacts of improved groundnut variety adoption on per capita consumption expenditure and on poverty reduction. The findings generally provide justification for continued public and private investment in groundnut research and outreach in Malawi.

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

Key words: groundnuts technology, propensity score matching, poverty, Malawi

1 Introduction

Agricultural growth is widely considered as the most effective means of addressing poverty in the developing world. Consistent with this notion, the Department for International Development (2003) estimates that a one percent increases in agricultural productivity could reduce the percentage of poor people living on less than 1 dollar a day by between 0.6 and 2 percent and that no other economic activity generates the same benefit for the poor. However, the key challenge in the developing country agriculture is how to increase agricultural productivity to meet food security needs for the growing population and to also reduce poverty and malnutrition, and to do it in a sustainable way. As reported by de Janvry et al (2001) the growth in production can not come from area expansion since that has already become a minimal source of output growth at world scale and negative source in India and Latin America. Thus growth in the production will have to come from growth in yields emanating from scientific advances offered by biotechnology and other plant breeding initiatives.

In most of the sub-Saharan Africa, agriculture remains large and the bulk of the poor are smallholders who benefit from it directly (. e.g., through increased agricultural profits) or indirectly (e.g., through increase in nominal income from other sources other than own agricultural production). Driven by hopes of a possibility of achieving an Africa Green Revolution through technological change, Research and Development efforts in Africa have led to the development and release of a number of improved crop varieties. It is widely believed that this led to substantial yield gains observed in the 1980s through to the 1990s. As expressed by Evenson (2003) 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. Evenson notes that 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.

Some impact assessment studies that were conducted following the release of such improved varieties for major crops (e.g., maize, rice) reported positive direct and indirect welfare effects of technology adoption on the farm households. For example, Kijima et al. (2008) in Uganda conducted a study on the impact of rice and found that rice adoption reduces poverty without deteriorating the income distribution. Other studies that show a positive impact of adoption of agricultural technologies include; Kassie et al (forthcoming), Winters et al. (1998); Mwabu et al. (2006); *de* Janvry and Sadoulet (2002), Otsuka, 2000; Rahman, 1999; David and Otsuka 1994, Lin 1999; Rahman 1999; de Janvry and Sadoulet 2001; Evenson and Gollin 2003, Foster and Rosenzweig 2003; Hossain et al. 2006; Janaiah et al. 2006; Mendola 2007; Becerril and Abdulai 2010; Wu et al. 2010).

The objective of the paper is to assess the role of improved groundnut technology adoption on consumption expenditure and poverty status measured by headcount index, poverty gap index and poverty severity index. Unlike previous studies that focused on major staple crops such as maize, wheat and rice largely in Latin America and Asia, this study focuses on the sub-Saharan Africa region The empirical question we would like to address is “Do improved groundnut varieties have the potential to reduce poverty? If yes, under which circumstances?

There are serious complexities associated with understanding the impact pathways through which agricultural technology adoption might affect household welfare. This is because crop production can affect household welfare both directly and indirectly. Consistent with this notion, de Janvry (2001) reports that crop production affects poverty directly by raising the welfare of poor farmers who adopt the technological innovation, through increased production for home consumption, more nutritious foods, higher gross revenues from sales deriving both from higher volumes of sales and high unit value products, lower production costs, lower yield risks, lower exposure to unhealthy chemicals and improved natural resource management. The indirect ways through which crop production affects welfare includes; (i) through the prices of food for net buyers and through employment and wages effects in agriculture. As well as employment and wage effects in other sectors of economic activity through production, consumption expenditures and savings linkages with agriculture. Indirect effects via employment creation are important for the landless farm workers, net labor selling smallholders and the rural-non agricultural and urban poor. Sadoulet and de Janvry (1992) show that relative magnitude of direct and indirect effects of technological change in agriculture on poverty can best be quantified through computable general equilibrium (CGE) models. This paper is however, based on a much simpler assumption of in the cross-sectional causal framework; thus the non-interference between units, or what Rubin (1978) calls the Stable Unit Treatment Value Assumption (SUTVA). This assumption rules out any *general equilibrium* effects where the *treatment* of one *unit* affects another's outcome. We thus assume that the source of the observed welfare effect of the adoption of new varieties is expected to be the result of direct benefits accruing from increased productivity, reduced production costs and increased marketed surplus.

We apply a Propensity-Score Matching (PSM) method to deal with the selection bias problem which is widely discussed in program evaluation. The PSM controls for differences in observable covariates that might influence the adoption decision and is based on the Conditional Independence Assumption CIA)[1]. However, as expressed by Ichino et al. (2008) and Rosenbaum (2002) the plausibility of CIA can be questionable under certain circumstances. Consequently they recommend that results based on the CIA should be put under scrutiny of sensitivity analysis to ascertain their robustness which we conduct in this paper. Most studies using PSM methods do not conduct this test. We thus conduct the rbounds test and a balancing test using the mean absolute standardized bias (MASB) between adopters and non-adopters as suggested by Rosenbaum and Rubin (1985).

The rest of the paper is organized as follows. Section 2 presents a discussion on groundnut production and utilization in Malawi while the impact evaluation challenges and the econometric framework is presented in section 3. In section 4 we present a description of the data and sampling methods. Results and discussions on the impact of improved groundnuts

[1] See Wooldridge (2002)

adoption on household consumption expenditure, poverty headcount, depth and severity are discussed in section 5. The conclusions and policy implications of the findings are presented in section 6.

2 Overview of groundnut Production and Significance in Malawi

Groundnut is an important legume crop for most parts of the world. Although, it 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.

Globally, 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). During the 2004/05-2007/08 period, about 40% of the total harvested groundnut area (260483 ha) was covered by improved groundnut varieties (Government of Malawi 2008). However, the impact of the adoption of improved varieties of groundnuts in Malawi has rarely been explored. Our hypothesis for the study is that improved groundnut adoption increases productivity, marketed surplus and consequently household income.

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 domestic market as raw groundnuts or processed into cooking oil.

Although produced in the entire country, the central and southern Agricultural Development Divisions (ADDs) of Kasungu, Lilongwe, 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.

However, the groundnut sector in Malawi is constrained by poor productivity as well as low marketed surplus from smallholder farmers. While attributed to poor crop management practices, the low yields are mainly due to low use of improved groundnut varieties. Even when improved varieties such as CG7 are adopted, they are highly susceptible to rosette attack hence their potential productivity gains are robbed by diseases attack. The adoption of improved groundnut varieties is said to be constrained by lack of awareness of the improved groundnut varieties and other constraints such as seed. Furthermore, the production of groundnuts has remained low in the last two decades due to the poor quality of groundnuts produced in Malawi, resulting from high aflatoxin levels. This further led to a reduction in the export volumes. Emphasis in current policies is focusing on supporting the production of high quality groundnuts with lower aflatoxin levels and on proper post-harvest handling techniques that reduce the build up of aflatoxin.

The key hypothesis for this study is that groundnut research and development efforts in Malawi have generated improved technologies that have significant potential for uplifting the poor out of poverty in Malawi. These economic benefits to producers and consumers result largely from higher yields , lower average production costs, lower food prices, and increased surplus that is marketed.

3 The Impact Evaluation Challenges and the Econometric Framework

The standard problem in impact evaluation involves the inference of the causal connection between the treatment and the outcome. There are two specific related problems with regards to evaluating the impact of an intervention on targeted individuals; thus (i) the selection bias problem and (ii) the problem of missing data for the counterfactual (see for example, Blundell and Costa Dias 2000 ; Wooldridge , 2001). The selection bias problem emanates from the fact that most program interventions are targeted at specific groups with specific characteristics and that the intervals targeted are not randomly selected. There is a problem of missing data because it is not possible to measure the impact on the same individuals as at each moment in time each individual is either under the intervention being evaluated or not and thus he or she can not be in both. This implies that we can not observe the outcome variable of interest for the targeted individuals had they not participated at the same time.

There is extensive literature describing developments in addressing the evaluation problem. Broadly, empirical literature categorises evaluation methods in five categories as follows: (i) The pure randomised experiments (ii) the natural experiment (iii) the matching method (iv) the selection or instrumental variable model which relies on the exclusion restriction and (v) the structural simulation model (for a detailed description of the methods see Blundell and Costa Dias, 2000).

The paper aims at indentifying the causal effect of adopting groundnuts on consumption expenditure and poverty using non-experimental data. As a consequence we follow Rubin (1974) Rosembam and Rubin (1983) Imbens and Angrist (1994) by applying the counterfactual outcomes framework also known as the Average Treatment Effect (ATE) framework. Under this framework it is assumed that each observational experimental unit with an observed outcome has ex-ante two potential outcomes: an outcome when under adoption that we denote by y_1 and an outcome when not under adoption which we denote y_0[2]. Let y_i be, for example, the *observed* overall expenditure for a household *i*. Thus y_1 and y_0 are two random variables representing, respectively, the potential expenditure level of household *i* when farmer grows groundnuts ($d_i = 1$) or does not grow ($d_i = 0$), respectively. For any household *i*, the causal effect of growing improved groundnuts on household expenditure is defined as: $y_1 - y_0$. However, the two potential outcomes can not be observed at the same time. We observe either y_1 or y_0, according to whether the household had grown improved groundnut or not; it is impossible to measure $y_1 - y_0$ directly. The average causal effect of adoption within a specific population (the average treatment effect) can be determined: $E(y_1 - y_0)$, with E as the mathematical expectation.

Several methods have been proposed to estimate the Average Treatment effect (ATE) and they include the matching methods based on propensity scores, as well as parametric methods based on Instrumental variable methods. The choice of method is largely driven by the assumptions made and the data available. For observational data an important assumption is the Conditional Independence Assumption (CIA) that states that conditional on X (observables), the outcomes are independent of the treatment (*d*) written as :

$$y_1, y_0 \perp d \mid X \qquad 3\text{-}1$$

The behavioral implication of this assumption is that participation in the treatment (growing improved groundnut) does not depend on the outcomes after controlling for the variation in

[2] We analyze four outcomes in the empirical section; percapita expenditure, poverty head count, depth of poverty and severity of poverty

outcomes induced by differences in *X*. A much weaker assumption also used for indentifiability of the causal effect of the treatment is what Imbens (2005) refers to as the unconfoundedness assumption, and which Rubin 1978 refers to as the ignorability assumption. The assumption is written as:

$$y_0 \perp d \mid X \qquad 3\text{-}2$$

If valid, the assumption implies that there is no omitted variable bias once *X* is included in the equation hence there will be no confounding.

The assumption of unconfoundedness (eq 4.2) is very strong, and its plausibility heavily relies on the quality and the amount of information contained in *X*. A slightly weaker assumption also associated with the treatment effect evaluation is referred to as the overlap or matching (common- support condition) assumption. The assumption ensures that for each value of *X*, there are both treated and untreated cases. The assumption is expressed as follows:

$$0 < \Pr[d = 1 \mid x] < 1 \qquad 3\text{-}3$$

This implies that there is an overlap between the treated and untreated samples. Stated the other way round this also means that the control and treated populations have comparable observed characteristics. Under the assumption discussed above (CIA and overlap) the average treatment effect on the treated (ATT) can be identified as

$$E(y_1 - y_0 \mid a = 1) = E(E(y_1 - y_0 \mid d = 1, X))$$

$$= E(E(y_1 \mid d = 1, X) - E(y_0 \mid d = 0, X) \mid d = 1) \qquad 3\text{-}4$$

where the outer expectation is over the distribution of *X* in the subpopulation of improved groundnut growing individuals.

In observational data it is not possible to calculate directly the difference in the outcome of interest between the treated and the control group, also known as the Average Treatment effect

(ATE) due to the absence of the counterfactual[3]. As a consequence data may be drawn from comparison units whose characteristics match those of the treated group. The average outcome of the untreated matched group is assumed to identify the mean counterfactual outcome for the treated group in the absence of a treatment

The propensity score matching method matches treated and untreated cases on the propensity score rather than on the regressor. The propensity score which is the conditional probability of receiving treatment given X, is denoted P(x) written as :

$$p(x) = \Pr[d = 1 \mid X = x] \qquad 3\text{-}5$$

An assumption that plays an important role in treatment evaluation is the balancing condition which states that ;

$$d \perp X \mid p(x) \qquad 3\text{-}6$$

This can be expressed alternatively by saying that for individuals with the same propensity score the assignment to treatment is random and should look identical in terms of their x vector.

Balancing tests and testing for the plausibility of the Conditional Independence Assumption

The main purpose of the propensity score estimation is to balance the observed distribution of covariates across the groups of adopters and non-adopters (Lee, 2008). The balancing test is normally required after matching to ascertain whether the differences in the covariates in the two groups in the matched sample have been eliminated, in which case, the matched comparison group can be considered a plausible counterfactual (Ali and Abdulai, 2010). Although several versions of balancing tests exist in the literature, the most widely used is the mean absolute standardized bias (MASB) between adopters and non-adopters suggested by Rosenbaum and Rubin (1985), in which they recommend that a standardized difference of greater than 20 per cent should be considered too large and an indicator that the matching process has failed. Additionally, Sianesi (2004) proposed a comparison of the pseudo *R2* and p-values of the likelihood ratio test of the joint significance of all the regressors obtained from

[3] The counterfactual is a condition in which the same household is observed under treatment and without treatment. In reality a household can only be observed under either of the two conditions at a time and not under both.

the logit analysis before and after matching the samples. After matching, there should be no systematic differences in the distribution of covariates between the two groups. As a result, the pseudo-*R2* should be lower and the joint significance of covariates should be rejected (or the p-values of the likelihood ratio should be insignificant).

Given how sensitive the quasi-experimental methods are to assumptions (selection on observables, exclusion restrictions, exchangeability, etc.), some kind of sensitivity testing is in order no matter what method is used. While the CIA allows the use of observed outcomes of control units to estimate the counterfactual outcome of treated units in the case of no treatment, Ichino et al. (2008) express that the plausibility of CIA can be questionable under some circumstances and that the CIA might fail in several ways and consequently results based on the CIA should be put under scrutiny of sensitivity analysis to ascertain their robustness to specific violations of the CIA. Thus we conduct the sensitivity analyses in this paper based on the Rosenbaum's method of sensitivity analysis as we believe CIA crucially depends on the possibility to match treated and control units on the basis of a large informative of pre-treatment variables.

4 Data and Descriptive Statistics

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, 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[4] in each district. Consequently this led to the

[4] Malawi is divided into eight ADDS that form different ago-ecological 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-divided into sections Extension agents called Field Assistants supervise at the section level

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) 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, household composition and characteristics, land and non-land farm assets, livestock ownership, household membership to different rural institutions, varieties and area planted, costs of production, yield data for different crop types, indicators of access to infrastructure, household market participation, household income sources and major consumption expenses.

5.2 Farm household characteristics

In this study, adopters are classified as farmers who planted at least one of the improved groundnut varieties (CG7 and Chalimbana 2002), and non-adopters are those who did not cultivate any of the improved groundnut variety. Table 1 reports descriptive statistics disaggregated by their adoption status. 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 are 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). 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 4.8 years(yrs). 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 (12.8yrs) than non-adopters (8.2 yrs).

There are also wide differences in terms of market access between adopting households and those that did not. For example, the proportion of farmers reporting that they received credit[5] (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 16,977 for non-adopting households.

< TABLE 1 ABOUT HERE>

There are trade-offs in technology between achieving direct and indirect effects. When land is unequally distributed and if there are market failures and conditions of access to public goods that vary with farm size, then the optimum farming systems will differ across farms. Small

[5] 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

holder may opt to adopt capital saving technologies, while larger farmers may prefer capital intensive technologies. Table 2 present the distribution of sample households according to land holdings and adoption status.

< TABLE 2 ABOUT HERE>

Consistent, with Bercerril and Abdulai (2010), the differences in the distribution of land between adopters and non-adopters suggest a positive correlation between the incidence of adoption and the ownership of land. The incidence of adoption is clearly higher among larger farmers compared to the smaller farmers. Such differences in land ownership between adopter and non adopters could also contribute to the disparities in welfare indicators between the two groups.

5 Results and Discussion

5.1 A descriptive analysis of the impact of improved groundnuts adoption

Table 3 depicts the descriptive statistics of key productivity indicators and the potential effect of adopting improved groundnut varieties. Results indicate that the area planted to improved groundnut varieties is about 0.26 acres per household whereas total area allocated to groundnuts is about 1.33 acres. Thus the area allocated to improved groundnut varieties accounts for about 20% of the total groundnut area. This is much lower than the average nation statistic of 40% of the area reported to be under improved varieties of groundnuts. However, households that cultivated some improved groundnut varieties allocated about 75% of their total groundnut land to improved varieties.

<TABLE 3 ABOUT HERE>

There are significant differences in production, productivity, variable costs, gross revenues and net incomes from groundnuts between farmers that grew improved varieties and those that grew local varieties. Results indicate that adopters achieved better yields (724kg/ha) compared to non-adopters (567kg/ha). While the cost of production does not differ significantly between the two groups of farmers, adopters of improved varieties obtain better profits (MK 31429) [6] than non adopters (MK 21957) due to the higher productivity.

Improved groundnut growers have about 30% more production and productivity compared to the non-adopters. As farmers adopt improved varieties, there is a reduction in variable costs by about 15% suggesting that adopters of improved varieties benefit from doing so by reducing costs of the production (though this is not statistically significant). The cost of production may reduce for a number of reasons, but in the case of this study it is partly attributed to the fact that improved varieties are early maturing and thus potentially reduce labor costs. As a consequence adopters have substantially higher net groundnut incomes accruing from groundnut production than non-adopters

Our interest is to assess the causal effect of technology adoption on well being. We start by estimating the average differences in the mean outcomes of interest (i) expenditure, (ii) incidence of poverty (iii) depth of poverty and (iv) severity of poverty between adopting households and non-adopters. Unlike other studies (e.g. Mendola (2007), who used per capita income to examine the impact of HYV of rice on income and poverty status, we rely on per capita consumption expenditure (expressed in Malawi Kwacha). The consumption expenditure components include six major categories including food grains, livestock product (such as meat), vegetables and other food items (such as sugar, salt), beverages (such as coffee, tea leaves), clothing and energy (such as shoes, kerosene) and social activities (contribution to churches or local organization, education and medical expenditure) over the twelve months (2007/08).

The threshold level of welfare that distinguishes poor households from non-poor households is the poverty line. Using a poverty line, a number of aggregate measures of poverty can be computed.

[6] The exchange rate at the time of the survey was about 1US$ = MK 145 (Malawi Kwacha)

A more general measure of poverty proposed by Foster-Greer-Thorbecke (1984) belongs to a class of poverty measures is given as:

$$p_{\alpha} = \frac{1}{n}\sum_{i=1}^{q}\left[\frac{z-y_i}{z}\right]^{\alpha} 1(y_i - z) \qquad \textbf{5-1}$$

Where z is the poverty line (z), y_i is expenditure per capita of the ith household measured in the same unit as z , n is the total number of individuals in the population, q is total number of poor individuals whose income is less than the poverty line, ,$1(.)$ is indicator variable which takes on a value of one if the income is below the poverty line and 0 otherwise and where α is a poverty aversion parameter which can take on values of 0, 1, and 2, providing three commonly used indices of poverty; poverty incidence as represented by the head count index, intensity by the poverty gap index and severity by the squared poverty gap index.

The poverty line is a subsistence minimum expressed in Malawi Kwacha based on the cost-of-basic-needs methodology. The National Statistics Office of Malawi reports that the Malawi poverty line is comprised of two parts: minimum food expenditure based on the food requirements of individual and critical non-food consumption. Food needs are tied to the recommended daily calorie requirement. Non-food needs are estimated based on the expenditure patterns of households whose total expenditure is close to the minimum food expenditure. Using this method, a poverty line is developed for the country. Individuals who reside in households with consumption lower than the poverty line are then labeled “poor”. Using the minimum food expenditure as an additional measure, we can identify the “ultra poor” households whose total consumption per capita on food and non-food items is lower than the minimum food expenditure. In this study we use the two poverty lines constructed by National Statistics Office to estimate the incidence of poverty as well as the incidence ultra poor households disaggregated by adoption status of improved groundnuts varieties[7].

Table 4 compares the unconditional incidence of poverty, the poverty gap, and the poverty severity of adopters and non-adopters which are computed using the Foster-Greer-Thorbecke (FGT) poverty measure discussed above. There is a significant difference between the adopter

[7] The national poverty line for Malawi is MK16, 165 while the ultra poor poverty line is Mk 10,025

categories in terms of welfare indictors A further close look at the distribution of consumption data shows that it is skewed to the left (Figure 1). After transforming the consumption variable into the logarithm form, the distribution is normalized but the t-test still shows a significant difference in consumption expenditure between adopters and non-adopters.

< FIGURE 1 ABOUT HERE>

About 72% of the households live below the poverty line. These poverty levels are much higher than the national poverty rate of 55% reported by the National Statistics Office (2004). The incidence of poverty is higher among non-adopters (74%) than it is among adopters (64%) indicating an unconditional headcount ratio of poverty for the adopters of about 10 percentage points lower, compared to non-adopters. About 35% of the households are ultra poor implying that 35% of the people among the sample households live in such dire poverty that they cannot even afford to meet the minimum standard of daily-recommended food requirement. The incidence of ultra poverty is also higher among non-adopters (40%) than among adopters (30%) suggesting that groundnut adoption is positively correlated with wellbeing.

< TABLE 4 ABOUT HERE>

5.2 An Econometric Analysis of the impact of improved groundnuts adoption

Although the unconditional summary statistics and tests in the tables above in general suggest that improved groundnut adoption may have a positive role in improving household well-being, these results are only based on observed mean differences in outcomes of interest and may not be solely due to improved groundnut adoption. They may instead be due to other factors, such as differences in household characteristics and the endowments discussed earlier. To measure the impact of adoption, it is necessary to take into account the fact that individuals who adopt improved varieties might have achieved a higher level of welfare even if they had not adopted. As a consequence we apply propensity score matching methods that control for these observable characteristics to isolate the intrinsic impact of technology adoption on household welfare.

5.2.1 Estimation of the Propensity Score

The logit estimates of the adoption propensity equation are presented in Table 5. The logit model has a McFadden pseudo R^2 value of 0.38 and log likelihood value of -204. It provides information about some of the driving forces behind farmers' decisions to adopt agricultural technologies where the dependent variable takes the value of one if the farmer adopts at least one improved groundnut technology and 0 otherwise. The results show that the coefficients of most of the variables hypothesized to influence adoption have the expected signs and they include factors such as the age of the of the head of household, the land holding size, access to credit, number of years of experience in groundnut farming and ownership of radio, among others.

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 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 have 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 small farmers. According to *de* Janvry et al (2001) small farmers will typically prefer new farming systems that are more capital-saving and less risky while large farmers would prefer new farming systems that are more labor saving and they can afford to assume risks. In this case small farmers seem to avoid improved varieties due to the high costs associated with the purchasing of improved seed.

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 finding is consistent with finding reported by for example, Feder and Umali (1990) and Cornejo and McBrid (2002) who they highlight access to credit as a key determinant of adoption of most agricultural innovations.

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 also be 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 to 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 knowledge about the intrinsic benefits of a new technology which they could use for judging whether or not to adopt the technology.

< TABLE 5 ABOUT HERE>

An important step in assessing the quality of matching is to perform tests that check whether the propensity score adequately balances characteristics between the treatment and comparison group units.

A visual inspection of the density distribution for the adopters and non-adopter in Figure 2 indicates that the common supports condition is satisfied. Histograms do not include the controls whose estimated propensity score is less than the minimum estimated propensity score for the treated units by common support restriction. As expected, the first intervals of diagram contain most of the remaining controls but the number of comparison units in the other bins is approximately equal to the number of treated units. Thus there is substantial overlap in the distribution of the estimated for the two groups.

FIGURE 2 ABOUT HERE

We further conduct balance test for the balancing of the distribution of relevant covariates between adopters and non-adopters before and after matching. Table 6 presents results of propensity score matching quality indicators before and after matching. Following Rosenbaum and Rubin (1985), we calculate the standardized difference, that is, the size of the difference in means of conditioning variables (between the adopters and non-adopter). Rosenbaum and Rubin (1985) recommend that a standardized difference of 20% or more should be viewed as large. As depicted in table 6, the standardize mean difference for overall covariates used in the propensity score is reduced by about 60% to 77% from about 21 before matching to about 4 after matching. Furthermore, the p-values of the likelihood ratio tests shows that the joint significance of the covariates was always rejected after matching where as it was never rejected before matching. The pseudo R^2 also dropped significantly from 15% percent before matching to about 2% or less after matching. This low pseudo R^2, low standardized bias, high total bias reduction, and the insignificant p-values of the likelihood ratio test after matching suggest that the specification of the propensity is successful in terms of balancing the distribution of covariates between the two groups.

< TABLE 6 ABOUT HERE>

5.2.2 Estimation of Average Adoption Effect (ATT): Matching Algorithms

Table 7 reports the estimates of the average adoption effects estimated using NNM and KBM methods. As a sensitivity analysis, the table reports estimates based on the single and five nearest neighbours, and the Epanechnikov kernel estimator with two different bandwidths. All the analyses were based on implementation of common support and caliper, so that the distributions of adopters and non-adopters were located in the same domain. As suggested by Rosenbaum and Rubin (1985), we used a caliper size of one-quarter of the standard deviation of the propensity scores. Bootstrap standard errors based on 100 replications are reported. Four outcome variables are used in the analysis: natural logarithm of per capita consumption expenditure (hereafter consumption expenditure), headcount index, poverty gap index and severity index. The consumption expenditure is transformed into logarithmic because it is right-skewed. The logrithmic transformation eliminates this skewedness (see Figure 1). The results indicate that adoption of improved groundnut varieties has a positive and significant effect on consumption expenditure and negative impact on poverty.

< TABLE 7 ABOUT HERE>

The adoption of improved groundnut varieties increases consumption expenditure by 2 percentage point per capita uses both algorithms. This is the average difference in consumption expenditure of similar pairs of households that belong to different technological status (i.e., adopters and non-adopters). The increase in consumption expenditure can help adopters reduce their poverty level. Depending on the specific matching algorithm used, the estimated impact of technology adoption on poverty reduction as measured by head count index is estimated to range 12-17 percentage points (see Table 7).

Adoption has also had an impact on reducing the depth and severity of poverty, depth of poverty as well as significantly decreasing inequality (severity) of poverty (Table 7). These findings are consistent with recent studies on the impact of modern crop varieties on household welfare. Hossain et al. (2006) and Mendola (2007) in Bangladesh, Janaian et al. (2006) in India, and Wu et al. (2010) in China showed that the adoption of improved rice varieties has a significant positive impact on household income and a negative impact on poverty status. Becerril and Abdulai (2010) using propensity score matching methods found that improved maize adoption significantly increases per capita expenditure and reduces poverty in Mexico. Kijima et al (2008) also showed that NERICA rice adoption reduces poverty without deterioration in income distribution in Uganda. Kassie et al. (2011) using PSM methods found that adoption of improved groundnut varieties in rural Uganda increase crop income and reduce poverty.

To gain further understanding of the impact of adoption on different groups of adopters, we also examined the differential impact of adoption by dividing households into quartiles based on farm size, and gender of the head of household. As observed in Table 9, the impact of adoption on consumption expenditure decreases with farm size. Interestingly, the gain in consumption expenditure and reduction in poverty is highest in the lowest farm-size quartile (1) and among male headed households. The adoption of improved groundnut varieties reduces the incidence of poverty among households with smallest holdings by about 67%. These findings suggest that groundnut is a pro-poor crop which can contribute to poverty reduction among the near landless households. However, the impact is more significant among male headed households where groundnut production reduces poverty by about 10%. This result is consistent with Becerril and Abdulai (2010), who found both the positive impact on per capita expenditure and negative impact on poverty with adoption of improved maize varieties declined with land size.

< TABLE 9 ABOUT HERE>

6. Conclusions

The relationship between agricultural technology adoption and welfare is assumed to be straight forward. However, quantifying the causal effect of technology adoption can be quite complex. This paper provides an ex- post assessment of the impact of adoption of improved groundnut technologies on consumption expenditure and poverty status measured by headcount index, poverty gap index and poverty severity index in rural Malawi. The challenge is to show whether changes in welfare indicators can be attributed to improved groundnut adoption. A counterfactual outcome framework of modern evaluation theory is used to consistently estimate the four selected outcome indicators.

Our results show that adoption of groundnut technology has a positive impact on consumption expenditures and negative on poverty reduction. Furthermore, our findings differentiated by farm size show that the potential gains from improved groundnut varieties are higher for the near-landless and lower for the larger farmers. Adopting improved groundnuts varieties increases income for the near-landless and helps them to overcome the poverty line as well. This can be interpreted as evidence that legume crops that require less capital in terms of inputs (such as fertilizer) can be an important tool for reducing poverty among the land poor.

Overall consistent with previous studies agricultural technology adoption can be a pathway to escape poverty in rural Malawi. Despite this, adoption is constrained by access to credit and information. Policy intervention that provides access to credit and information will increase diffusion and level of adoption.

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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
Groundnut area	0.47 (0.04)	1.49(0.09)	0.72 (0.04)	-1.02(0.09)***
Area under improved groundnut (ha)	0.00	1.11(0.98)	0.26 (0.67)	-1.11 (0.01)***
Groundnut production (kg)	206.(17)	308(27)	254 (16)	102.(32)***
Groundnut yield (kg/ha)	567(37)	724(60)	641(35)	157.(70)***
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)
Total family 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 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)

Table 2: Distribution of sample households by landholding and adoption status

Quartiles	Land size range	Adopters		Non-adopters	
		Frequency	Percentage	Frequency	Percentage
1st quartile	0-0.51	15	10	133	30
2nd quartile	0.52-0.89	26	17	121	28
3rd quartile	0.90-1.33	44	29	108	25
4th quartile	1.34-6.7	67	44	78	18

Table 3: Comparative farm-level economic benefits from groundnut production among groundnut producers

Variable	Non-adopters (n=173)	Adopters (n=152)	Total (n=325)	Difference
Groundnut area (ha)	1.48 (0.09)	1.20(0.08)	1.33 (0.06)	0.29(0.12)**
Area under improved groundnut (ha)	0.00	1.11(0.98)	0.26 (0.67)	1.11 (0.98)***
Groundnut production (kg)	174.(11)	210(15)	190 (9)	36 (18)**
Groundnut yield (kg/ha)	567(37)	724(60)	641(35)	157 (70)***
Gross value of production (MK per ha)	26897 (1914)	35443 (3157)	30887 (1806)	8546 (3594)**
Variable costs (MK per ha)	5321 (558)	4585 (484)	4977 (373)	736 (748)
Groundnut net-income (MK per ha)	21957 (1678)	31429 (2944)	26379 (1658)	9471(3287)**

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

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

Poverty measures	Non-adopters (n=442) 75%	Adopters (n=152) 25%	Total (n=594)	Difference
Per capita expenditure (MK)	13257	16057	13983.	2800***
Ln (percapita expenditure)	9.3009	9.5051	9.3539	-0.2042***
Poverty Headcount (%)	74	64	72	-9.89**
Ultra-Poverty Headcount (%)	40	30	35	10*
Poverty gap index	0.32	0.24	0.29	-0.08***
Severity gap index	0.17	0.12	0.16	-0.05***

Note: For the above calculations MK 16165 per person per day is used as poverty line while the ultra poor poverty line is Mk 10,025. These are basic needs poverty lines for Malawi during the survey period. Statistical significance at the 99% (***) confidence levels.

Source: Authors' computation using FGT poverty formula

Table 5: Determinants of adoption of improved groundnuts- Estimated coefficients

Variables	**Estimates**	
	Coef	SE
Gender of head (1=Male, 0=Otherwise)	-0.1521	0.1716
Age of head (yrs)	-0.0131**	0.0055
Education of head (yrs)	0.0094	0.0197
Household size	0.0196	0.0312
Land holding size (acres)	0.0949**	0.0389
Access to credit(1=yes, 0=otherwise)	0.6616***	0.1612
Distance to the main market (km)	0.0173	0.0141
Distance to an ag.ric office	0.0202	0.0214
Number of years lived in village	-0.0003	0.0050
Contact with NGO extension worker (1=yes, 0=otherwise)	0.0031	0.0037
Number of years of experience in groundnut farming	0.0213***	0.0068
Amount of non-farm income (MK)	0.0000	0.0000
Livestock ownership (1-yes, 0=otherwise)	0.0000	0.0000
Proportion of land allocated to tobacco (%)	-0.0205**	0.0081
Ownership of radio (1=yes,0= otherwise)	0.2968**	0.1451
Constant	-2.1004***	0.4016
Number of interviews	583	
Pseudo R2	0.375	
Model Chi-square	245.23***	
Log likelihood	-204.402	

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

Table 6: Propensity score matching quality indicators before and after matching and sensitivity analysis (adoption effect on per capita expenditure, MK)

Matching algorithms	Pseudo R^2 before matching	Pseudo R^2 after matching	LR X^2 (*p-value)* before Matching	LR X^2 (*p-value*) after Matching	Mean standardized bias before matching	Mean standardized bias after matching	(Total)% |bias| reduction
[a]NNM	0.148	0.020	95.26 (0.00) ***	7.53 (0.912)	21.157	7.969	62.3
[b]NNM	0.148	0.012	95.26 (0.00) ***	4.62 (0.990)	21.157	6.142	71.0
[c]KBM	0.148	0.009	95.26 (0.00) ***	3.63 (0.887)	21.157	4.920	76.7
[d]KBM	0.148	0.008	95.26 (0.00) ***	3.19(0.999)	21.157	4.884	76.9

[a]NNM = single nearest neighbor matching with replacement, common support, and caliper (0.03)

[b]NNM = five nearest neighbors matching with replacement, common support, and caliper (0.03)

[c]KBM = kernel based matching with band width 0.03, common support

[d]KBM = kernel based matching with band width 0.06, common support.

Table 7. Impact of improved groundnut adoption on per capita expenditure and poverty status

Matching algorithm	Outcome	Outcome mean		ATT
		Adopters	Non-adopters	
[a]NNM	Per capita expenditure (MK)	9.582	9.381	0.200 (2.10)***
	Head count ratio	0.586	0. 761	-0.174 (-2.67)***
	Depth of poverty	-0.088	0.074	-0.162 (-1.64)*
	Severity of poverty	0.529	0.513	-0.015 (0.10)
[b]NNM	Per capita expenditure	9.582	9.414	0.167 (2.10)***
	Head count ratio	0.586	0. 761	-0.129 (-2.29)***
	Depth of poverty	-0.088	0.489	-0.37(-1.63)*
	Severity of poverty	0.529	0.509	0.020 (0.13)
[c]KBM	Per capita expenditure	9.582	9.415	0.166 (2.23)***
	Head count ratio	0.586	0.708	-0.121 (-2.20)***
	Depth of poverty	-0.088	0.047	-0.135(-1.63)*
	Severity of poverty	0.529	0.519	0.009 (0.05)
[d]KBM	Per capita expenditure	9.582	9.415	0.166 (2.29)***
	Head count ratio	0.586	0.709	-0.122 (-2.25)***
	Depth of poverty	-0.088	0.047	-0.135(-1.67)
	Severity of poverty	0.529	0.523	0.006 (0.03)

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

The number of observations on common support for probit model for adopters (non-adopters) are138 (416),

[a]NNM = single nearest neighbor matching with replacement, common support, and caliper (0.03)

[b]NNM = five nearest neighbors matching with replacement, common support, and caliper (0.03)

[c]KBM = kernel based matching with band width 0.03, common support

[d]KBM = kernel based matching with band width 0.06, common support.

* Figures in parentheses at *t*-values

Table 8: Sensitivity Analysis for Average Treatment Effect results for selected algorithms

Matching algorithm	Outcome	ATT	Critical level of hidden bias (Γ)
[a]NNM	Per capita expenditure (MK)	0.200 (2.10)***	1.30
	Head count ratio	0.174 (-2.67)***	1.55
KBM[c]	Per capita expenditure (MK)	0.166 (2.23)***	1.25
	Head count ratio	-0.121 (-2.20)***	1.35

[a]NNM = single nearest neighbor matching with replacement, common support, and caliper (0.03)

[c]KBM = kernel based matching with band width 0.03, common support

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

* Figures in parentheses at *t*-values

Table 9: Differential impact of adoption by farm size and years of experience in groundnut farming

Stratified by farm size (quartiles)	Mean impact on household consumption	Mean impact on headcount ratio	Mean impact on depth of poverty	Mean impact on severity of poverty
1	0.927(3.0)***	-0.667 (-4.0)***	-1.066 (-2.77)***	1.209 (1.58)
2	0.273 (1.39)	-0.318 (-2.32)***	-0.296 (-1.81)*	0.151 (-0.94)
3	0.145 (0.86)	-0.129 (-100)	-0.123 (-0.88)	-021 (0.22)
4	0.058 (0.38)	-0.075 (-0.57)	-0.058 ((0.27)	0.061 (-0.13)
Stratified by gender	**of the household head**			
Male	0.219 (1.94)**	-0.104 (-1.31)	-0.200 (-1.80)	-0.140 (-0.88)
Female	0.347 (1.64)	-0.071 (-0.51)	-0.112 (-0.69)	-0.237 (-1.85)

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

* This is based on a much smaller sample size involving groundnut growers only

Figure 1 Distribution in Consumption expenditure before and after transformation

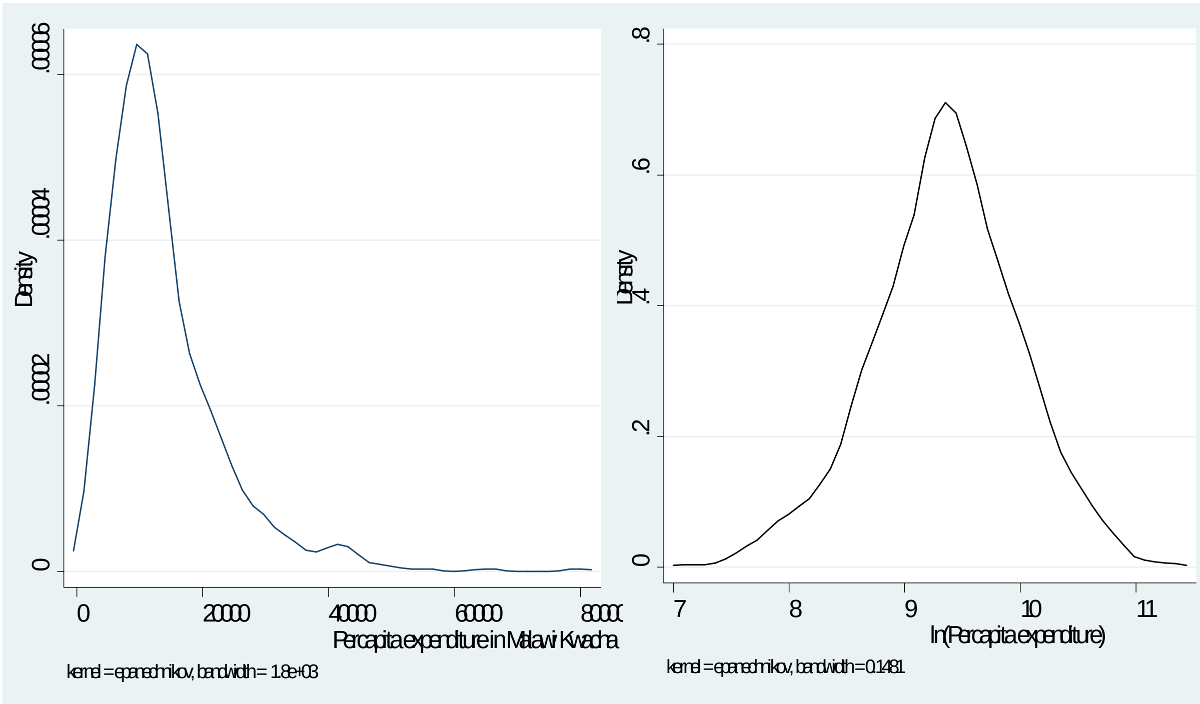
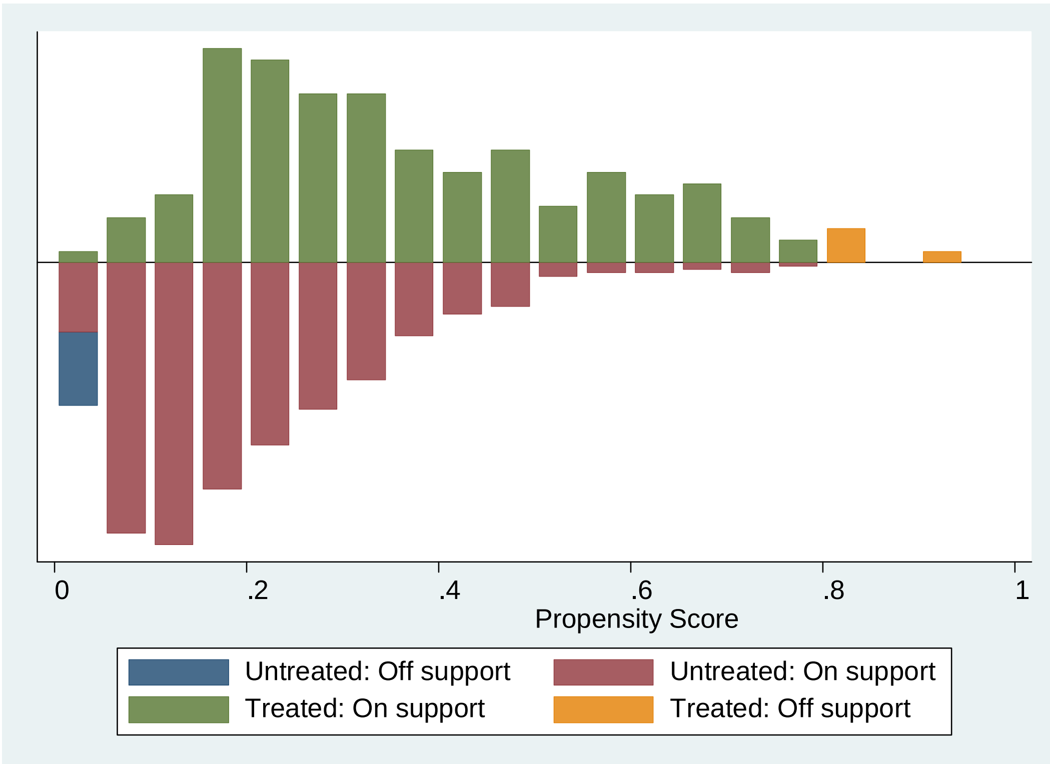


Figure 2: Propensity score distribution and common support for propensity score estimation



Note: Treated: on support” indicates the observations in the adoption group that have suitable comparison. “Treated: off support’ “indicates that the observations in the adoption group that do not have a suitable comparison.