Program evaluation of agricultural input subsidies in Malawi using treatment effects: methods and practicability based on propensity scores

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Millennium Challenge Account - Malawi

22 February 2010

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April 2010

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Abstract

The study evaluates the impact of two agricultural input subsidies in Malawi during the 2003/04 and 2006/07 production periods on household income. The study employs quasi-experimental econometric techniques that use propensity score matching to control for selection bias on beneficiaries. A household model for each dataset is estimated together with Average Treatment Effects on the Treated. The evidence suggest that the matching mechanism performs well in evaluating the impact of the starter pack program which had a significant negative impact on household income compared to the refined agricultural input subsidy program which showed significant positive impacts on household income.

JEL Classification: C31, D13, H23, H43, I38

Keywords: Fertilizer Subsidies; Propensity Score Matching; Complex Survey Design; Average Treatment Effects on the Treated

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1.0 INTRODUCTION

Almost 85% of Malawi's population belongs to farm (peasant) households and agricultural production and productivity are often dependent on their performance as farmers. Malawi being a labor intensive country, the importance of these farmers is often undermined and understanding the determinants of their welfare, functionality of markets in their communities and the interventions that are more effective in improving their livelihoods are of vital importance both to Government and policy makers. This approach helps policy makers in developing strategies of poverty alleviation that seek to address problems faced by peasant farmers.

However, once such strategies are developed they are faced with lack of sustainability partly because there is failure to understand how *agrarian* institutions work and how to promote such agrarian societies up the life cycle ladder. Some of these problems arise due to lack of an understanding that peasant households are single institutions where decisions are made holistically on production, consumption and reproduction over time (Sadoulet and de Janvry, 1995). These decisions require the functioning of markets within and outside their social stratum.

In this case, one need to understand why households are always semi-commercialized in the sense that, even when markets are working, they still keep part of their production for home consumption or utilize part of their household labor for their own use. Secondly, on the markets, one needs to understand why rural markets fail in forming backward and forward linkages to the household entity. As we will see in later sections, the failure to comprehend these two important questions necessitates the formulation of poor policies that do not maximize the utility of the householder's social welfare function.

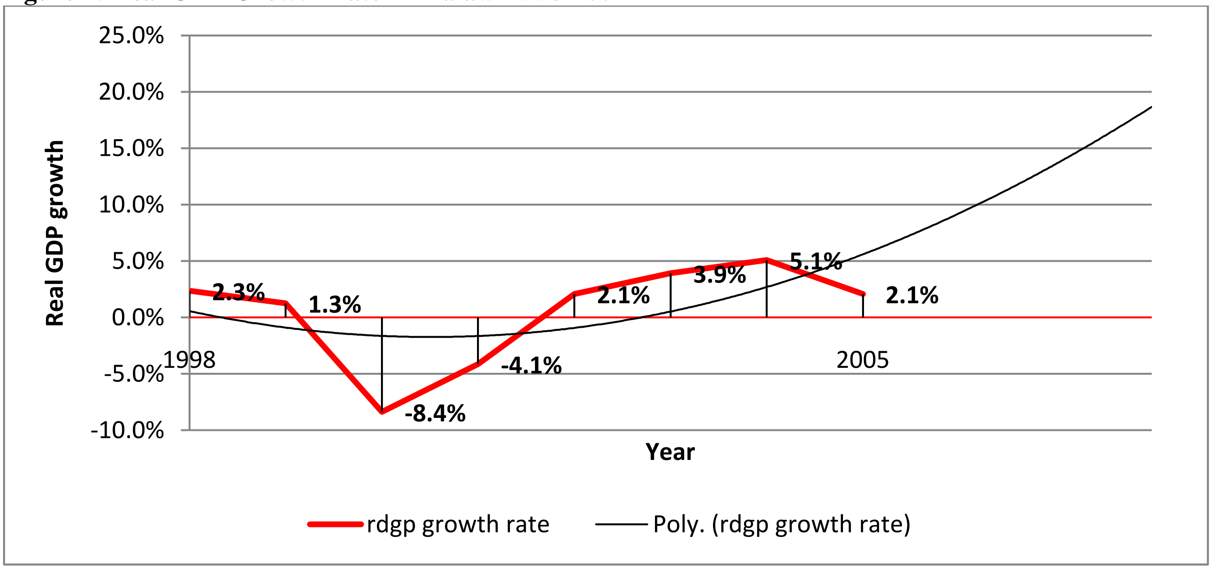
The Agricultural Input Subsidy Program in Malawi and Intended Effects

The goal of the agricultural input subsidy programs in Malawi is to improve agricultural production and productivity of smallholder farmers for both food and cash crops thereby reducing the vulnerability of food insecurity and hunger. These input subsidy programs have been in existence since Malawi attained its independence from Britain in 1964.

The Starter Pack (TIP) program is one such agricultural input program that was implemented from 1998-2004. The program provided 10-15 kg of fertilizers and ample hybrid maize seed, free of charge, worthy of planting 0.1 hectares of land. It targeted between 33-96% of rural smallholder farmers which was scaled down from being a universal subsidy in 1998/99 to a targeted input program in 2003/04 production periods (Harrigan, 2003; Levy, 2005).

There are variable conclusions concerning the success of the starter pack (TIP) program from different researchers and data sources. Real GDP growth in Malawi since 1998 to 2005 has been variable averaging 0.5% per annum (see figure 1). Since the backbone of the Malawi economy heavily relies on agriculture, the variability in real GDP growth rate signifies the failure of the starter pack program in improving agricultural production and productivity.

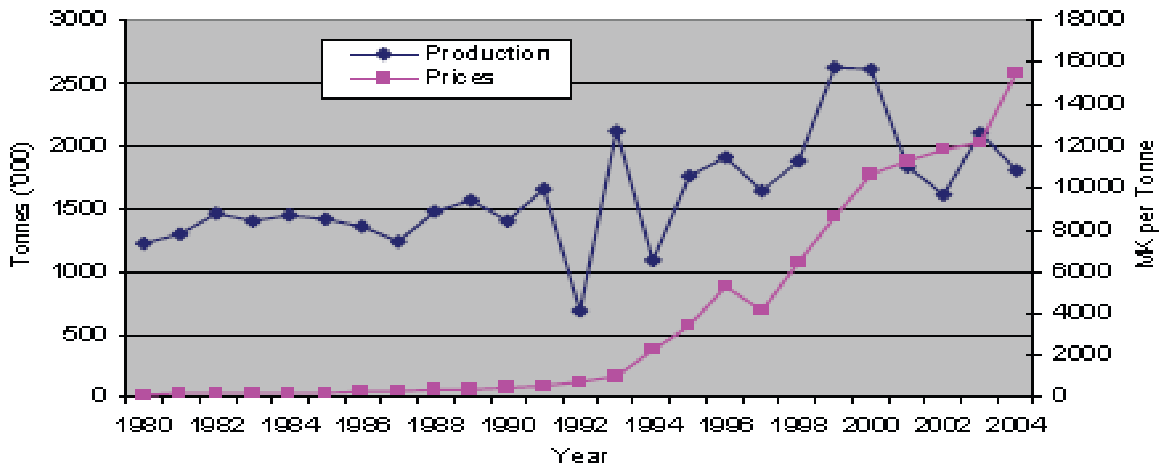
Figure 1: Real GDP Growth Rate in Malawi 1998-2004



Source: Malawi Annual Statistics Data 1998-2005

Chirwa et al (2006, p. 3) argues that maize production since 1990 has been uneven and increasingly disappointing depicting an agricultural growth rate of 2.2% per annum between 2000 and 2004. Maize prices have also been increasing amid falling and variable maize production during the same period (see figure 2).

Figure 2: Maize Production and Prices (Nominal) in Malawi, 1980-2004



Source: Chirwa (2006)

Dorward et al (2008), on the other hand, argues that the impact of higher maize prices are a dilemma as only about 10% of Malawi maize producers are net sellers of maize while 60% are net buyers. Peters (2006) further argues that the success of the starter pack program was affected by famine in various parts of the country during the 2001/02 and 2004/05 production periods. We argue in this paper that the variability in both real GDP and maize production in the late 1990s and early 2000s was partly a result of the small quantities of the starter pack program that negatively impacted on maize production and hence affected real GDP growth.

The 2006/07 input subsidy program, on the other hand, was a continuation from the 2005/06 revised program that allocated 2 million of improved seed and 3 million fertilizer coupons to all districts in Malawi. The distribution of fertilizers initially targeted 1 million marginalized farmers that were unable to purchase agricultural inputs. The selection of households in targeted areas was done by Village Development Committees (in consultation with the entire members of the village) to select households that would benefit three coupons from the input program: two to buy back 50 kg of basal fertilizer (23:21:0 or NPK) and 50 kg of top dressing fertilizer (Urea) at MK950, each; and the third coupon to be used in exchange for a 10 kg bag of improved maize seed worthy of planting one acre of land. For tobacco smallholder farmers, the approach was similar only that they would buy back Compound D and CAN fertilizers. These input subsidies for tobacco farmers were only implemented during the 2005/06 production period.

However, in this paper we concentrate on maize farmers to compare the differences in impacts between the 2003/04 and 2006/07 production periods. As we will notice later on, not all beneficiaries in this improved input subsidy program received both coupons for basal and top dressing fertilizer. It is reported that there were some significant diversion of coupons in some areas whereby households ended up receiving one fertilizer coupon in order to expand the number of beneficiaries within a village (Dorward et al, 2008).

It should be noted at the outset that, amid all these problems faced by the householder, the goal of input subsidies in Malawi are mainly meant to increase household income, reduce food insecurity and hence poverty reduction. Therefore, assessing the direct impacts of such a program on household income or expenditures on the targeted beneficiaries becomes a good decision tool for policy makers. Evaluating the complexities beyond the farm gate requires an understanding of the transformative and network effects and whether the householder is geared towards competing with established businesses such as large scale commercial farmers. In most studies, the rural smallholder farmer is always referred to as a subsistence farmer (Levy, 2005; Dorward et al, 2008).

Study Objectives and Hypotheses to be Tested

The agricultural system in Malawi is seasonal and several months in a given year are left idle and farmers have to seek alternative ways of generating income for their survival. Government interventions in this case become very important tools to boost the income of the household in lean periods. Government either would initiate a public works program or provide safety nets with emphasis on cash transfers to marginalized smallholder households.

Several evaluations have been conducted to assess the impact of agricultural input subsidy programs in Malawi which have either been descriptive/qualitatively inferred (Gregory, 2006; Dorward et al, 2008; Minot and Benson, 2009) or the econometric methods employed have not controlled for any measurement errors or unobserved heterogeneity on the beneficiaries (Bohne, 2009; Ricker-Gilbert, 2009).

The argument in this paper is intended to inform policy makers on the impact of input subsidy programs on household income by using *quasi-experimental econometric* techniques. The process adopted estimates a conventional household model to determine the effectiveness of two input subsidy programs by controlling for treatment effects. To our knowledge, no study has been done that employs such a technique to assess program intervention effects of the input subsidy program in Malawi.

The study objectives, therefore, are twofold. The first one seeks to evaluate government interventions using *treatment evaluation* techniques that focus on evaluating periodic panel datasets with the aim of assessing intervention effects on the goal of the agricultural input subsidy program. Secondly, to provide quantitative evidence that complementing the input subsidy program with programs that seek to address market failures directly impact on household income, positively.

The second objective aims at assessing other determinants of household income such as access to basic services (roads, markets) and how they impact on household income. This approach will inform agricultural policy makers of the need to include additional program objectives when implementing the next agricultural input subsidy program.

The key hypotheses to be tested in this paper, therefore, are as follows:

(a) The 2003/04 starter pack (TIP) program that provided 10-15 kg of fertilizer subsidy had a *significant negative impact* on household incomes.

(b) The 2006/07 agricultural input subsidy that provided 100 kg worth of fertilizer had a *significant positive impact* on household incomes.

(c) Access to key basic services such as roads and markets in rural areas negatively impact on household income in rural areas.

The sections of the paper are as follows: section 2 looks at literature review. Section 3 outlines the methodology to be adopted in this paper. Section 4 looks at results and findings. Lastly, section 5 concludes and provides recommendations for future policy interventions.

2.0 LITERATURE REVIEW

It has been noted that different researchers often ask the wrong questions and use wrong methodologies when assessing agricultural empirical questions that target the poor or less privileged in any given society. In any assessment or evaluation of a public intervention seeking to improve a given social welfare function of the disadvantaged groups, it is important to ask the question whether the targeted beneficiaries were better or worse off after the intervention was implemented. It becomes irrelevant, in my view, to consider the cost implications of such interventions especially when the intervention proved to be a success.

With regard to the second Pareto Optimality principle[1], Government's role is to redistribute wealth and if such distribution is done in a transparent and accountable manner without making other players worse off then it would be an added advantage. On the issue of methodology, Lalonde (1986) argues that standard non-experimental techniques such as regression, fixed effects, and latent-variable selection models are either inaccurate or sensitive to model specification. Thus, employing such techniques to assess the impact of an intervention may be subjected to measurement errors and selection bias.

Other researchers have attempted to compare smallholder farmers with commercial farmers in which those who received subsidized fertilizers have been compared with yield responses of farmers who pay commercial prices (Ricker-Gilbert et. al, 2009). This depicts a lack of understanding of how smallholder households behave and a clear eulogy to measurement error. According to Sadoulet and de Janvry (1995), on one hand, smallholder farmers are usually semi-commercialized and usually production is at a subsistence level. They only sell if they have excess production and this depends on their production and consumption needs. Large commercial farmers, on the other hand, rely on markets and have different objectives than a rural smallholder subsistence farmer.

For one to make such a comparative analysis it has to be done at a similar level playing field. For instance, access to effective and efficient agricultural extension services, educational programs, market and transport systems and credit markets are vital and necessary components if we are to compare commercial and smallholder farmers. Commercial farmers are usually strategically positioned and can easily access these basic services. They usually have access to skilled personnel that are well conversant with latest technologies of

[1] The second theorem of welfare economics states that if all consumers have convex preferences and all firms have convex production possibility sets, any Pareto efficient allocation can be achieved as the equilibrium of a complete set of competitive markets after a suitable redistribution of initial endowments (Gravelle and Rees, 2004)

improving agricultural production unlike rural households that utilize traditional experience to perpetuate their agrarian methodologies. As such, utility functions for smallholder and commercial farmers are incomparable.

Therefore, arguments assuming that smallholder farmers who receive subsidized inputs at discounted prices through the Government may obtain similar output responses as commercial farmers may be an assumption that does not reflect reality. This hypothesis on its own is an oversimplification and would lead to gross measurement errors, model misspecification and selection bias. This approach would and has always led to the non-acceptance on the application of input subsidies on marginalized households and thus has confused policy makers and development partners of the need to subsidize inputs to the underprivileged groups.

It also follows that a smallholder farmer will only have an incentive to use a productive asset as efficiently as possible regardless of the purchasing price if and only if the farmer has access to the same conditions faced by commercial farmers. In this case, access to knowledge, information and years spent on education become important. Some studies, for example, have found that fixed costs (distant to market) and variable costs (price per unit) may affect market participation (Key et al, 2000; Bellemare et al, 2006). Others have also shown that access to credit and insurance may be constraints being faced by farmers in order for them to purchase inputs at reasonable prices (Kherallah et al, 2000; Croppenstedt et al, 2003; Jayne et al, 2003).

Another misconception that is frequently being abused is the combination of a social welfare function with profit-maximizing behavior. Gregory (2006) argues that input subsidy vouchers are an income transfer to the farmer from Government, donor or any other implementing agency but also a transfer that can be realized through private sector participation (see also

Kelly et al, 2003). This assumption, however, has its own problems and in this paper we identify two: firstly, the role of Government is to raise taxes from private entities and distribute wealth to marginalized households or communities.

Since private sector entities are profit driven and liable to additional taxation, the process affects the '*laissez-faire*' assumption of the free operation of market forces and becomes one that continuously add transaction costs that become unsustainable rendering the intervention too expensive to public coffers. Government comes in to correct a market failure – a failure that was created by the private sector in the first place that profiteers a social good.

Secondly, since other factors such as access to basic services may affect the distribution of agricultural inputs to smallholder farmers, the involvement of private sector participants creates *rent-seeking behavior* amongst private players as the business involved is risk-free guaranteed by Government thereby adding more on the transaction costs.

As Shultz (1945) indicates, smallholder farmers in developing countries may be poor but are efficient. It, therefore, depends on the quality and quantity of agricultural inputs being supplied to the targeted beneficiaries and whether they would have access to the same privileges that a normal commercial farmer would receive. Kelly and Murekezi (2000) and Duflo et al (2008) also note that application of fertilizer in maize, for example, improves the yield if the application is made in right quantities and using the correct methods. In other words, the rate of return to fertilizer application is positive but varies by region.

The other mistake that researchers make is to employ panel data sets which may have been developed using different set of conditions. Therefore, any assessment of the impact of fertilizer subsidy before and after an intervention is made, for example, cannot be justified by looking at different periods or time series but rather creating a counterfactual within the same period and dataset. This reduces potential selection bias by utilizing the same dataset to create a control group (Dehejia and Wahba, 1999; Browyn and Maffioli, 2008).

As evidenced by Ricker-Gilbert et al (2009), one problem could be that the same respondents have different farm size within and between agricultural seasons. Thus, in order to avoid such plot-level unobserved heterogeneity, the study considers periodic analysis of each input subsidy production period in order to contain for any measurement errors. Recent econometric tools are available to make such an assessment and it is this approach that will be adopted in this paper in order to assess the effectiveness of public interventions targeting the poor.

3.0 METHODOLOGY

Model Specification

The main objective of the input subsidy programs before and after 2004/05 was to increase agricultural productivity and food security. The overall goal of the program was to promote economic growth and reduce vulnerability to food insecurity, hunger and poverty. The 2006/07 Agricultural Input Subsidy Program (AISP) was implemented through the distribution of fertilizer vouchers of which the beneficiary had to contribute MK950 per voucher of fertilizer and exchange a voucher of seed free of charge. In later years, the contribution made by beneficiaries reduced to MK500 during the 2009/10 production period. In comparison to the TIP program, targeted smallholder farmers were given all inputs free of charge but in small quantities.

To assess the impact of such interventions in the given seasons or fiscal years, we will employ an empirical model on household food security. The model adopts Sadoulet and De Janvry (1995) household model with less efficient markets where the household problem is to solve simultaneously allocation of resources between production, consumption and work decisions given household characteristics. In its structural form, the household problem is to maximize utility $u(\cdot)$ with respect to consumption and work decisions subject to a given production function $\mathrm{g}(\cdot)$ and household characteristics:

$$\begin{aligned} \max_{q_a, x, l, c_a, c_m, c_l} &= u\left(c_a, c_m, c_l; \mathbf{z}^h\right) \\ s.t. \quad & g\left(q_a, x, l, \mathbf{z}^h\right) \end{aligned} \tag{1a}$$

In equation (1a), utility is maximized given consumption goods (agricultural goods c_a and manufactured goods c_m), home time c_l and household characteristics $\mathbf{z}^h$ subject to a household production function q_a and a set of fixed and variable inputs (x, l). The empirical model assumes a linear function and in a reduced form format:

$$y_i = y_i(\mathbf{G}, \mathbf{P}, \mathbf{H}, \mathbf{E}, \mathbf{C}, \mathbf{W}, \mathbf{S}, \mathbf{L}) \tag{1b}$$

In equation (1b), y_i is the outcome of interest – household real expenditure per household which is a proxy for household income per capita; $\mathbf{G}$ is a vector of government interventions (starter pack program or TIP of 2003/04, agriculture extension services, Agricultural Input Subsidy Program of 2006/07); $\mathbf{P}$ is a vector of prices (tobacco auction price, maize grain price, maize flour price, fertilizer, casual labor – supply and demand prices, charcoal, transport, and price index of other consumables); $\mathbf{H}$ is a vector of household characteristics (age, gender, education, health status, sources of lighting and cooking, farm size, livestock assets, access to portable water, wellbeing); $\mathbf{E}$ is a vector of economic characteristics (market access, distance to market, area of residence, access to road surface); $\mathbf{C}$ is a vector of community characteristics (belonging to an association/cooperative, access to agricultural credit, irrigation scheme, access to small and large markets): $\mathbf{W}$ is a vector of weather conditions (availability of rain); $\mathbf{S}$ is a vector of seasonal effects (lean period, dry period, harvest period, year of interview); and $\mathbf{L}$ is a vector of location effects (agricultural division).

Data Description and Management

The study utilizes raw household data from the 2004/05 second Integrated Household Survey (IHS2) and the 2006/07 Agricultural Input Subsidy Survey (AISS). The variables within each vector of interest of the household model in equation (1a) and (1b) are calculated and averaged over districts. The prices calculated are district level averages from both household and community databases. A number of robustness checks are conducted which include controlling for outliers, management of duplicate records and conducting principal component analysis to create a livestock index.

Our focus is mainly on rural households since they are more capable of benefiting from the agricultural input subsidy program than households that live in urban areas. Using the IHS2 data out of a sample of 11280, about 9840 households reside in rural areas, which is our point of reference. About 60% of households who reside in rural areas reported to have benefited from the starter pact (TIP) program compared to 11.6% in urban areas (1440)[2]. The focus on rural areas also hinges on the household model employed as we assume that households in rural areas are semi-commercialized and thus would expect their behavior to be similar from one area to the next.

A follow-up survey was conducted in May/June 2007 re-interviewing 3,298 households in 175 EAs. Out of this sample, 2,874 households were previously interviewed in the IHS2 survey. This dataset will be referred in this study as the AISS. The survey design process was the same as the one adopted under IHS2. After controlling for duplicate records, the AISS

[2] IHS2 Survey data

sample size was reduced to 2,937 households of which 1,205 households reported to have benefited from the input subsidy. Based on this response, 57% reported receiving both 100 kg of basal and top dressing fertilizers through the Government's AISP. The analysis of the impact of the AISP will, therefore, be based on respondents who received 100 kg of fertilizer based on the goal of the AISP.

The 2006/07 AISS database has a lot of missing values which constrains the analysis to only those variables that can be used to estimate the household model. In order to complement some of the missing variables, the study uses 2004/05 IHS2 survey data on some key variables such as annual household real expenditure and selected community based variables such as access to safe water, electricity, distance to and availability of markets in the community, among others. These common variables are assumed to be constant in 2006/07 as they were during the 2004/05 IHS2 survey. Annual household real expenditures per capita are projected based on real GDP growth rates experienced since 2003/04 to 2006/07 fiscal years to match the current household income levels in 2006/07 production season. The impact of the AISP will thus be assessed on whether it was effective in positively contributing to increased food expenditures in 2006/07 production year.

Treatment Effects Framework

The problems assessed in sections 1 and 2 above in evaluating the impact of interventions on input subsidies in Malawi warrant different methodologies to be looked into. It is more relevant to assess the impact of an intervention based on '*with or without*' the intervention scenario of the sample or population that benefited from the project. As Browyn and Maffioli (2008) notes, this provides a rigorous strategy of identifying statistically robust control groups on non-participants. Though the ideal evaluation of an intervention necessitates the creation of a treatment or control group, this approach cannot be applied on human beings prior to the beginning of the intervention.

Rosenbaum and Rubin (1983) propose '*propensity score matching*' (PSM) as a method that can be used to measure the impact of interventions on outcomes of interest. Propensity score matching is a method used to reduce selection bias in the estimation of treatment or intervention effects with observational data sets. The methodology developed is used to assess a counterfactual in a given set of observational data just like in any scientific experiment where the same sample can be used to assess the impact on the outcome if the treatment was not administered. Unlike interventions made on human beings, it is not likely that an intervention can be administered in one case and also assess the outcome on the same individual if the intervention was not administered, hence the need for propensity score matching.

The effect of treatment evaluation on policy formulation is direct because if an intervention is successful it can be linked to desirable social programs or improvements in existing programs through reviews. The aim of adopting such a process is to enable policy makers assess the objectives or goals of the intervention. According to Cameron and Trivedi (2005), the standard problem of treatment evaluation involves the '*inference of a causal*' connection between the treatment and the intended outcome.

The idea of measuring the effect of a treatment or intervention requires constructing a measure that compares the average outcomes of the treated and non-treated groups. Rosenbaum and Rubin (1983) show that if the exposure to treatment or an intervention is random within cells defined by the vector $\mathbf{x}_i$, it is also random within cells defined by the values of the propensity score. Therefore, given a population or sample of units i the propensity score or the conditional probability of receiving a treatment given $\mathbf{x}_i$ is:

$$p(\mathbf{x}) = \Pr\{D = 1|\mathbf{x}\} = E[D|\mathbf{x}] \tag{2}$$

Once propensity scores are known, we then can calculate the *Average effect of Treatment on the Treated* (ATT) as follows:

$$\begin{aligned} ATT &= E\{y_{1i} - y_{0i}|D_i = 1\} \\ &= E\{E\{y_{1i} - y_{0i}|D_i = 1, p(\mathbf{x})\}\} \\ &= E\{E\{y_{1i}|D_i = 1, p(\mathbf{x})\} - E\{y_{0i}|D_i = 0, p(\mathbf{x})\}|D_i = 1\} \end{aligned} \tag{3}$$

In equation (3), y_{1i} assumes the individual receives a treatment or intervention and y_{0i} is a counterfactual if the same (or similar) individual receives no treatment. In its simplest form the average treatment effect is estimated simply by subtracting the average outcome for the treated with the average outcome for the untreated.

This hypothesis requires two key assumptions namely: the *conditional independence* assumption and the assumption of *unconfoundedness*. The first assumption states that conditional on $\mathbf{x}_i$, the outcomes are independent of treatment. In other words, participation in the program intervention does not depend on the outcome. The unconfoundedness assumption, which in some cases is referred to as the Balancing condition, is necessary if we are to identify some population measures of impact (Rosenbaum and Rubin, 1983; Cameron and Trivedi, 2005). Given the overlap or matching assumption in equation (2), the independence assumption ensures that for each value of the vector $\mathbf{x}_i$, there exist both treated and non-treated cases. The propensity score measure can be computed given the data $(D_i, \mathbf{x}_i)$ through either a probit or logit regression.

Propensity Score Matching

The key to the balancing property between the treated and un-treated is to identify comparable groups or counterfactual by focusing on key household attributes or characteristics. The agricultural input subsidy program mainly focuses on promoting food security or household income. The matching methodology calculates propensity scores based on the following logit model:

$$TIP = f(hhage, fhh, poor) \tag{4}$$

The rationale for selecting these household attributes is based on the selection criteria that the input subsidy program follows when distributing fertilizer coupons to intended beneficiaries. The beneficiaries are considered marginalized and vulnerable and mostly the selection criterion is based on whether the householder is headed by a female, regarded as poor or by the age variable. Furthermore, the area of residence (rural or urban) is the key identifier of an agricultural input subsidy and the focus of analysis will only consider householders that reside in rural areas.

The advantage of the survey data used is that the observations were randomly drawn and thus the treatment will not be subjected to a situation where we are unable to identify a control group. In the 2006/07 AISS dataset, the creation of a control group takes advantage of the distributional problems of the input subsidy program where not all beneficiaries received both basal and top-dressing fertilizers. In doing so, we are able to create a control group for the treated. However, this may create contamination as the control group still receives fertilizer but only the basal type. The bias created may affect the significant difference between the beneficiaries and non-beneficiaries. Nonetheless, we may not run into such a problem as the yields that a farmer would get by just applying one type of fertilizer are significantly lower than yields when both types of fertilizers (basal and top-dressing) are applied.

Balancing Properties

One critical area of PSM literature is to assess whether the matching mechanism adopted is balanced in the allocated blocks/cells. Fifteen (15) and nine (9) blocks/cells have been created for models 1 and 2, respectively. We present tests for equality of means for each of the three regressors presented in equation (4) within each block. The results are presented in table 1 (annex I) and the logit regression in table 2. The results show that all variables are balanced in each block and we cannot reject the null hypothesis that the differences in mean of the treated and controls are different from zero. Thus, the balancing properties when estimating propensity scores in both models are satisfied.

Using calculated propensity scores as defined in equation (2) and (4) is not enough to estimate average treatment effects of an intervention (Dehejia and Wahba, 1999; Cameron and Trivedi, 2005; Becker and Ichino, 2009). The reason is that the propensity score is usually a continuous variable and the probability of observing two units with exactly the same propensity score is in principle not possible. A number of methodologies have been proposed in the literature with the aim of overcoming this problem (see Cameron and Trivedi, 2005). In this evaluation exercise, however, we will consider only four most common methods widely used: nearest neighbor matching, radius matching, kernel matching and stratification (or interval) matching[3].

We plot density functions for the treated and control groups to see whether the matching of scores is over a reasonable number of observations. The probability density functions for the

[3] Details on how these matching estimators are calculated can be found in Cameron and Trivedi, 2005, p.871-879

propensity scores are displayed in figures 3, 4 and 5 (annex II) for models 1 and 2, respectively, obtained from *attnd*, *attr*, and *attk* STATA commands. The results show that the mean propensity score between the treated and control group is well distributed in both models. The distribution of treatment also performs well when one uses radius and kernel matching techniques.

4.0 MODEL ESTIMATION AND RESULTS

Robustness Checks

Table 3 (annex III) present robustness checks on the data for the two models to be estimated. We first check whether the models have no omitted variables. We use the Ramsey RESET test using powers of the fitted values of the food expenditure dependent variable. The results show that the two models are affected by omitted variables. Since the two datasets are limited on the number of variables that can be generated from each database, we still estimate the models given the present variables.

On functional form and heteroskedasticity, we use Cameron and Trivedi decomposition of the IM test that tests for heteroskedasticity, skewness and kurtosis. The results for both models suggest that there are problems of heteroskedasticity and skewness. We will therefore, use weighted least squares and a log-linearised model to correct for skewness.

The Breusch-Pagan/Cook-Welsberg test is used to test for overall heteroskedasticity in the two models and the results show that both models are affected by heteroskedasticity. This further substantiates the need to report Huber/White heteroskedasticity consistent standard errors.

We test for multicollinearity on the variables of interest using variance inflation factors (VIF). In both models there is evidence of multicollinearity and the variables with a high variance inflation factor (VIF) are dropped. One common variable in both equations is the square of household age.

A new regression model is estimated using ordinary least squares (OLS) and corrected based on problems identified by the above common misspecification tests. We also test for endogeneity and the results show that the model suffers from an endogeneity problem and one of the suspected parameters is the household age variable (hhage) which has a positive sign as we would expect that as age of an individual increases, the propensity of being food insecure is high.

We, therefore, should expect a negative sign for the household age variable. In this case we expect that the household age variable is correlated with the error term or there is a measurement error being influenced by a reverse causation of the dependent variable. In this case, the two models may present biased and inconsistent parameter estimates.

Instrumental Variables

To correct our problem we identify an instrumental variable for the household age variable in order to obtain consistent estimates. A good instrument is one that is correlated with the endogenous household age variable, conditional on other covariates, but also at the same time not correlated with the error term. We follow this process in identifying the instrumental variable for hhage and test the correlation coefficients between hhage and three related exogenous variables – elderly, madult and fadult. The correlation coefficients are presented in table 4 (annex III) and show that the elderly variable is strongly correlated with hhage (0.6382, model 1; 0.5405 model 2) and has a strong significant p-value.

We further test the validity of the selected instrumental variable (elderly) and the results are presented in table 3. The results show that we cannot reject the null hypothesis that the elderly variable is exogenous in both models (*p-values 0.2812 and 0.9032*) and hence not correlated with the error term. In this case, the elderly variable is a good instrument for the hhage variable. The model to be estimated will, therefore, follow two stage least squares (2SLS) estimation to provide consistent parameter estimates.

Regression Results

The results for the estimated instrumental variable or 2SLS models are presented in tables 5 and 6 (see annex IV) together with the estimated average treatment effects on the treated (or ATT) for the input subsidy intervention based on Becker and Ichino (2009) algorithms. The goodness of fit shows that in the first model using IHS2 data the explanatory variables explain about 33% of the variation on the dependent variable and 27% in the second household model.

Tables 7 and 8 (see annex V) present an average propensity score difference estimator between the treated and the control group based on equation (3) and show the number of treated and control groups for each matching mechanism adopted. The ATT estimators presented in tables 7 and 8 are average treatment effects based on all blocks/cells created as outlined in table 9 (annex VI). We now present the regression results based on the hypotheses to be tested.

Hypothesis 1: Impact of the 2003/04 Starter Pack (TIP) Program on Household Income

After controlling for complex survey design and 2SLS estimation, the results show that those who benefited from the Starter Pack (TIP) program, holding other factors constant, had a significant negative impact of approximately 0.0819 (8.2%) or reduced annual household income per capita by MK1399.00 (1399 Malawi Kwacha).

Overall the results obtained after controlling for treatment effects (nearest neighbor, radius, kernel matching and stratification) taken together, also give evidence of a significant negative treatment effect in the ranges of MK1228-MK2521 associated with the TIP subsidy when evaluated with control or comparison groups, *ceteris paribus*. Note that the ATT results are close to the coefficient estimate for the TIP impact given in our household model of MK1399[4].

The results are not surprising and concur with evaluations made by government and some researchers on the impact of the TIP subsidy as not being effective in reducing poverty and food insecurity (Dorward et al 2008; Ricker-Gilbert et al 2009). The size of the package distributed to targeted households contributed significantly to the negative impact as well as corrupt practices identified by Peters (2006). It is more likely that the application of fertilizers were done to fit a householder's farm size that was more than 0.1 hectares. In such circumstances, yield would generally be low or equivalent to a situation where no fertilizers are applied to a particular field. This could have been necessitated by poor extension services that did not advise targeted farmers on how to apply the subsidized fertilizer.

Hypothesis 2: Impact of 2006/07 Agricultural Input Subsidy Program on Household Income

The second household model results (table 6) show that those who benefited from the full subsidy of the AISP, holding other things constant, had a significant positive contribution of 0.082 (8.2%) or MK1679 more towards household income than those who did not benefit from the AISP. Overall, the results obtained after controlling for ATT also give significant evidence (except the ATTR) on the effect of treatment on the beneficiaries. Those who received a full subsidy from Government, *ceteris paribus*, experienced a positive impact in

[4] Note that the coefficient estimates in log-terms for annual household real expenditure per capita are transformed using the exponential function and obtain the difference between the treated and untreated.

the ranges of MK1567-MK1705 (ATT of 0.075-0.083) associated with the 2006/07 AISP when evaluated without the intervention comparison group. Again the results support observations by other researchers about the positive impact that the revised agricultural input subsidy program had on household incomes and in reducing food security in Malawi (Dorward et al, 2008).

Hypothesis 3: Impact of Basic Services on Household Income

The study also evaluated the impact of market access on annual household income per capita. Three key variables were included in each household model that looked at the impact of roads, market access and distance to the market on household income. The study results are similar in both models and show that those who had access to large markets, holding other things constant, had a significant negative impact of 0.1218 (or 12.2%) and 0.154 (or 15.4%), in 2003/04 and 2006/07 production periods, respectively, than those who did not. This is surprising as one would expect that farmers with better access to large markets would be better off than those who do not. The reason is that these markets are secondary markets and are far away from main markets in the three cities in the country. As such, farm gate prices tend to be below the smallholder farmer's long-run marginal cost curve in rural areas.

This also concurs with the fact that lack of or existence of poor basic services such as markets in rural areas greatly affect household production and consumption decisions (see Dorward et al, 2008 and Chirwa et al, 2006). This is supported by the negative impact that distances to markets have on household income and registered -0.0022 (or -0.22%, significant at 1% level) during 2003/04 and -0.0019 (or -0.2%) during the 2006/07 production seasons, *ceteris paribus*.

As for roads, during the 2003/04 production season the variable of interest was dropped due to multicollinearity. During the 2006/07 production season, however, the road variable registered, *ceteris paribus*, a significant negative impact of 0.163 (or 16.3%) for communities that had access to only a dirt road maintained on a regular basis. Unpaved roads usually raise transportation costs and thus lower farm gate prices as intermediate buyers have to cover their marginal costs. This also supports the argument of the need to improve basic services in rural areas in order to lower transaction costs and maximize the benefits from any social program through proper marketing mechanisms.

5.0 CONCLUSIONS AND RECOMMENDATIONS

The paper has demonstrated on how we can use treatment effects to evaluate the impact of public interventions based on independent datasets. The study has also employed algorithms developed by Becker and Ichino (2009) to assess input subsidy effects on household food expenditures. The main conclusions from this study can be summarized as follows: the impact of the input subsidy programs in Malawi becomes stronger as policy makers improve on the quantities of inputs subsidized. The benefits can further be maximized if such programs are complemented with projects aimed at improving access to basic services in the targeted areas such as roads and markets.

There is clear evidence of a significant negative impact of the 2003/04 Starter Pack (TIP) program and significant positive impact of the AISP on household income when we use treatment effects. The differences are a result of Government improving on the quantities of fertilizer used by smallholder farmers and improving on the distribution to marginalized beneficiaries. The adopted approach is important as it controls for selection bias that may result from measurement errors and model misspecification.

Access to basic services in rural areas such as large markets and unpaved roads negatively impact on the availability of household income. We conclude that interventions geared towards complementing input subsidies should be supported with interventions aimed at improving basic services such as the development of markets and roads in rural areas. In concluding, we offer a few recommendations based on the results obtained in this study when assessing the impact of input subsidies in Malawi or any other program intervention aimed at improving national economic growth and poverty reduction. Some of the recommendations are based on weaknesses envisaged when evaluating the two NSO survey datasets in this study.

In order to effectively, efficiently, independently and successfully evaluate public interventions the following recommendations should be adopted by program implementers and collectors of national statistical data:

i) Relevant tracking mechanisms should be adopted to collect primary data on key variables that would be affected by the intervention in question. In most cases a *household model* would be the best starting point of determining the type of information to be tracked and how that dependent variable will be affected by the intervention in question.
ii) In order to assess the impact of public interventions effectively and independently it is important that implementers of such programs should link up with the National Statistical Office personnel in country in order to formulate the type of questions to be tracked as they may provide a '*low cost*' independent platform of collecting the same information by simply including specific '*program intervention*' sections on existing questionnaires that they randomly collect.
iii) Follow-up surveys conducted by the National Statistical Office should promote the continuance collection of original questionnaire variables collected in the Integrated Household Survey or at least tracking of common variables relevant to household characteristics in order to be able to evaluate the impact of a specific intervention based on the household model. This observation is based on the different sets of variables that

were collected in the 2006/07 follow-up survey on assessing the impact of agricultural input subsidies in Malawi that were different from the original IHS2 survey.

Finally, the study also encountered some problems that are beyond its scope. We did not run into any significant problems of missing data with the IHS2 database but were significant in the follow-up 2006/07 panel survey. This may have affected the consistency of the results obtained when running the second household model.

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7.0 ANNEXES

Annex I: Two Sample t-tests for Mean Propensity Score and Logit Regression Results

Table 1: Two Sample t-test with Equal Variances

H_0:Mean Propensity Score not different for treated and controls

Variable Name	Block	Difference estimate		t-statistic		p-value	
		Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Mean pscore	8		0.002				
	9	0.000	-0.002	-0.31	-1.40	0.76	0.18
	10	0.000	-0.002	-0.86	-0.74	0.39	0.46
	11	-0.001	0.002	-1.61	1.27	0.11	0.21
	12	-0.001	-0.002	-1.84	-0.84	0.07	0.41
	13	-0.001	-0.001	-1.73	-0.29	0.08	0.77
	14	-0.001	0.001	-1.93		0.05	
	15	0.001	-0.001	1.15	-1.12	0.25	0.26
	16	0.000	-0.020	0.35	-1.66	0.73	0.10
	17	-0.001		-1.65		0.10	
	18	0.000		-0.14		0.89	
	19	-0.001		-0.95		0.34	
	20	0.000		0.47		0.64	
	21	0.000		-0.32		0.75	
	22	0.000		0.06		0.95	
	23	-0.003		-0.96		0.34	
hhage	8		2.800				
	9	-0.140	-2.221	-0.72	-1.40	0.48	0.18
	10	-0.115	-2.594	-1.00	-0.75	0.32	0.46
	11	-0.157	1.843	-1.25	1.27	0.21	0.21
	12	-0.184	-0.132	-1.57	-0.05	0.12	0.96
	13	-0.192	-0.595	-1.47	-0.28	0.14	0.78
	14	-0.101	0.600	-0.60		0.55	
	15	-0.006	-1.152	-0.03	-1.13	0.98	0.26
	16	0.042	-2.208	0.21	-1.66	0.84	0.10
	17	-0.346		-1.59		0.11	
	18	-0.203		-0.73		0.46	
	19	-0.119		-0.46		0.65	
	20	0.477		1.45		0.15	
	21	-0.399		-0.89		0.37	
	22	-0.065		-0.11		0.91	
	23	-1.072		-0.82		0.42	
fhh	8		0.000				
	9	0.017	0.000	0.75		0.45	
	10	0.011	0.000	0.59		0.56	
	11	0.015	0.000	0.61		0.54	

H_0:Mean Propensity Score not different for treated and controls

Variable Name	Block	Difference estimate		t-statistic		p-value	
		Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
	12	0.010	-0.038	0.59	-0.59	0.56	0.55
	13	0.005	0.000	0.31	0.00	0.76	1.00
	14	-0.011	0.000	-0.41		0.68	
	15	0.019	0.000	0.64		0.52	
	16	0.001	0.000	0.02		0.99	
	17	0.029		0.89		0.38	
	18	0.035		0.75		0.46	
	19	-0.011		-0.31		0.76	
	20	-0.076		-1.37		0.17	
	21	0.060		0.83		0.41	
	22	0.015		0.23		0.82	
	23	0.022		0.15		0.88	
poor	8		0.000				
	10		0.000				
	11		0.000				
	12		0.038		0.59		0.55
	13		0.000		0.00		1.00
	14		0.000				
	15		0.000				
	16		0.000				

Table 2: Logit Estimates for Mean Propensity Score if Householder Resides in Rural Area

Model 1	TIP	Model 2	aissf
hhage	0.0271	hhage	0.0040
	(0.00)***		(0.31)
fhh	0.1463	fhh	-0.4596
	(0.01)**		(0.00)**
		poor	-0.6821
			(0.00)***
_cons	-0.7612	_cons	0.3336
	(0.00)***		(0.08)
N	*9573*	*N*	*1171*
pR-sq	*0.035*	*pR-sq*	*0.022*

Note: Balancing property is satisfied

Marginal Effects; t-statistics in parenthesis

(d) for discrete change of dummy variable from 0 to 1

=" p<0.05 ** p<0.01 *** p<0.001"*

Annex II: Probability Density Functions for Propensity Scores

Figure 3: Density Function for Mean Propensity Score

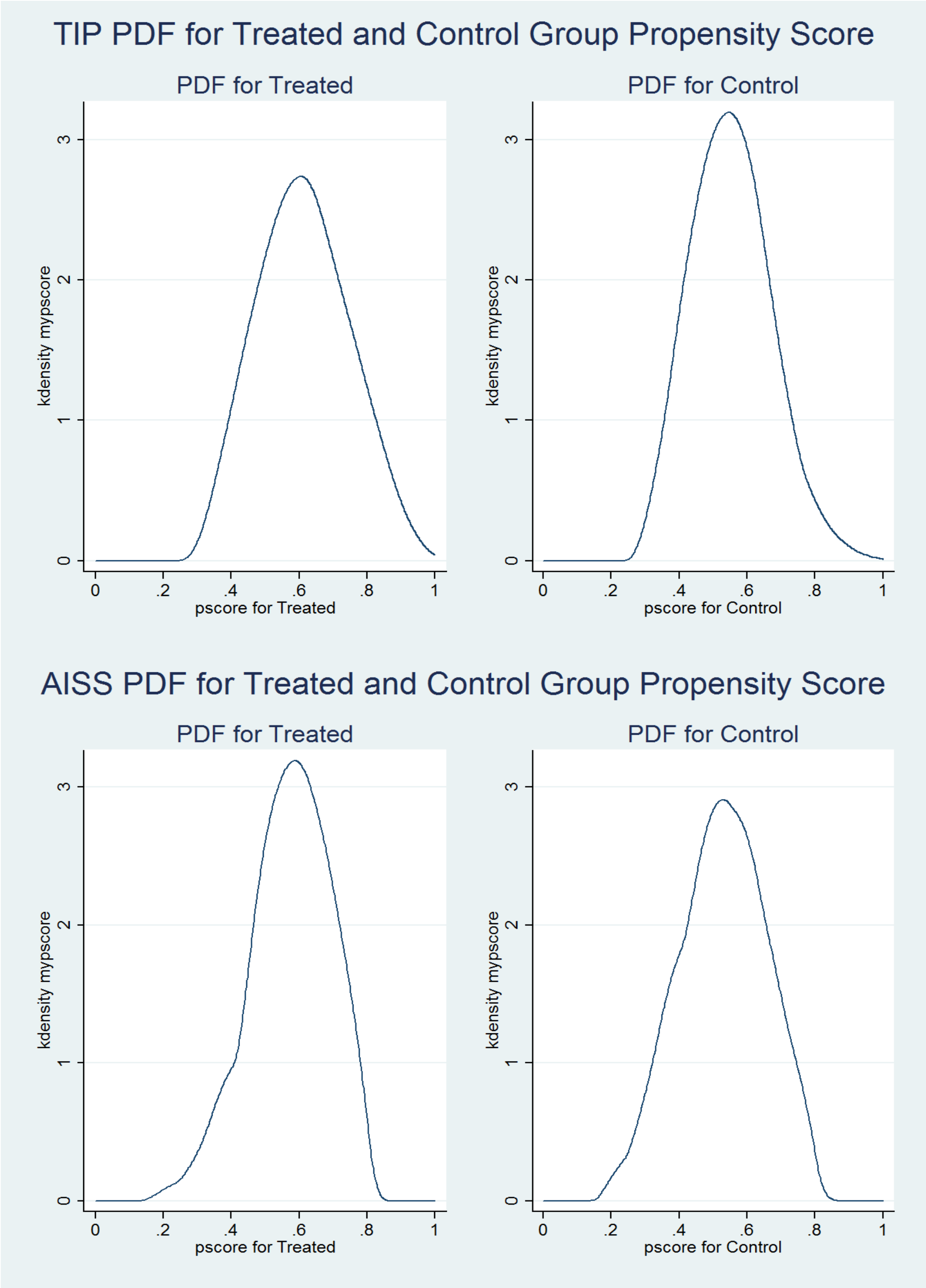


Figure 4: Model 1

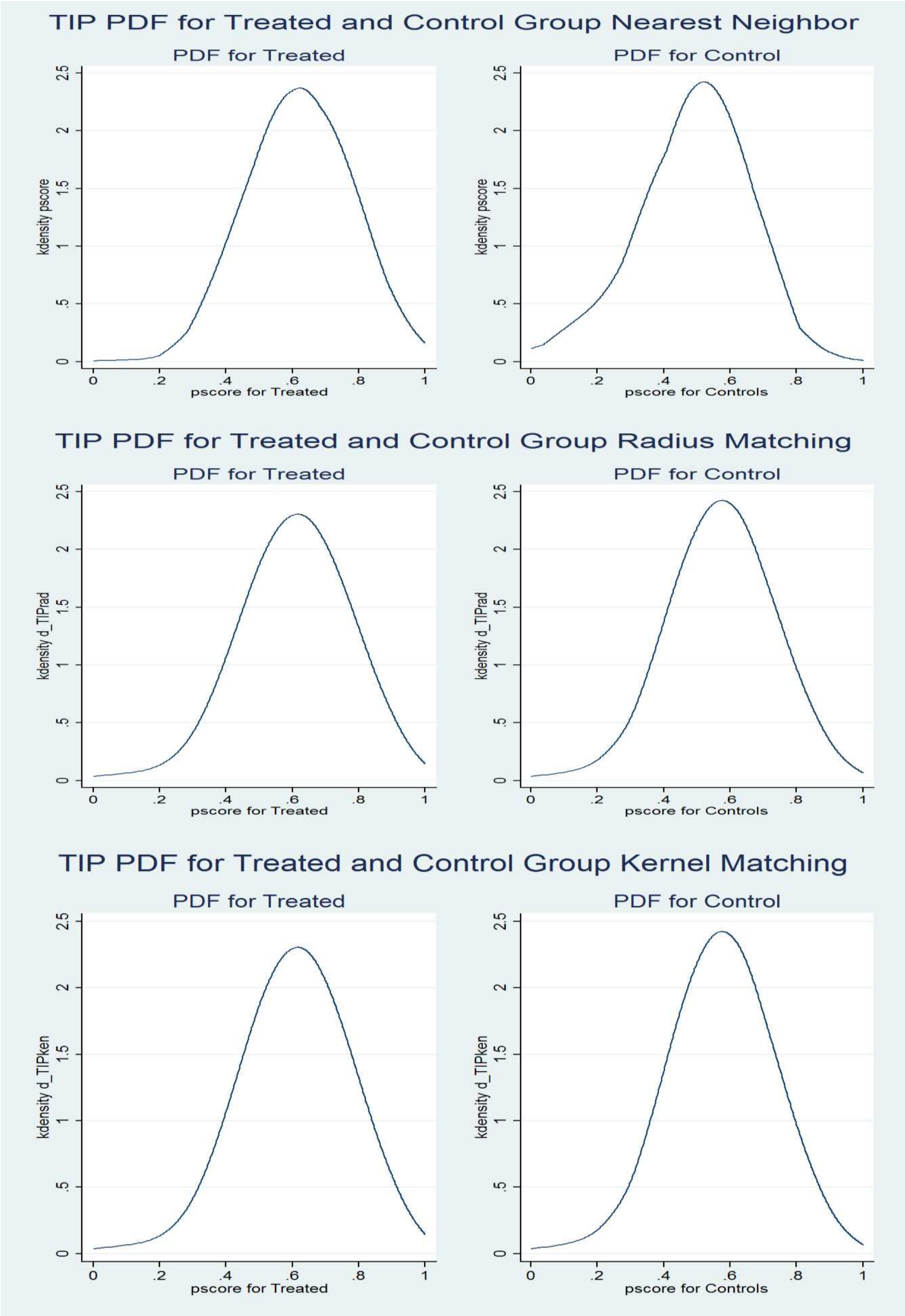
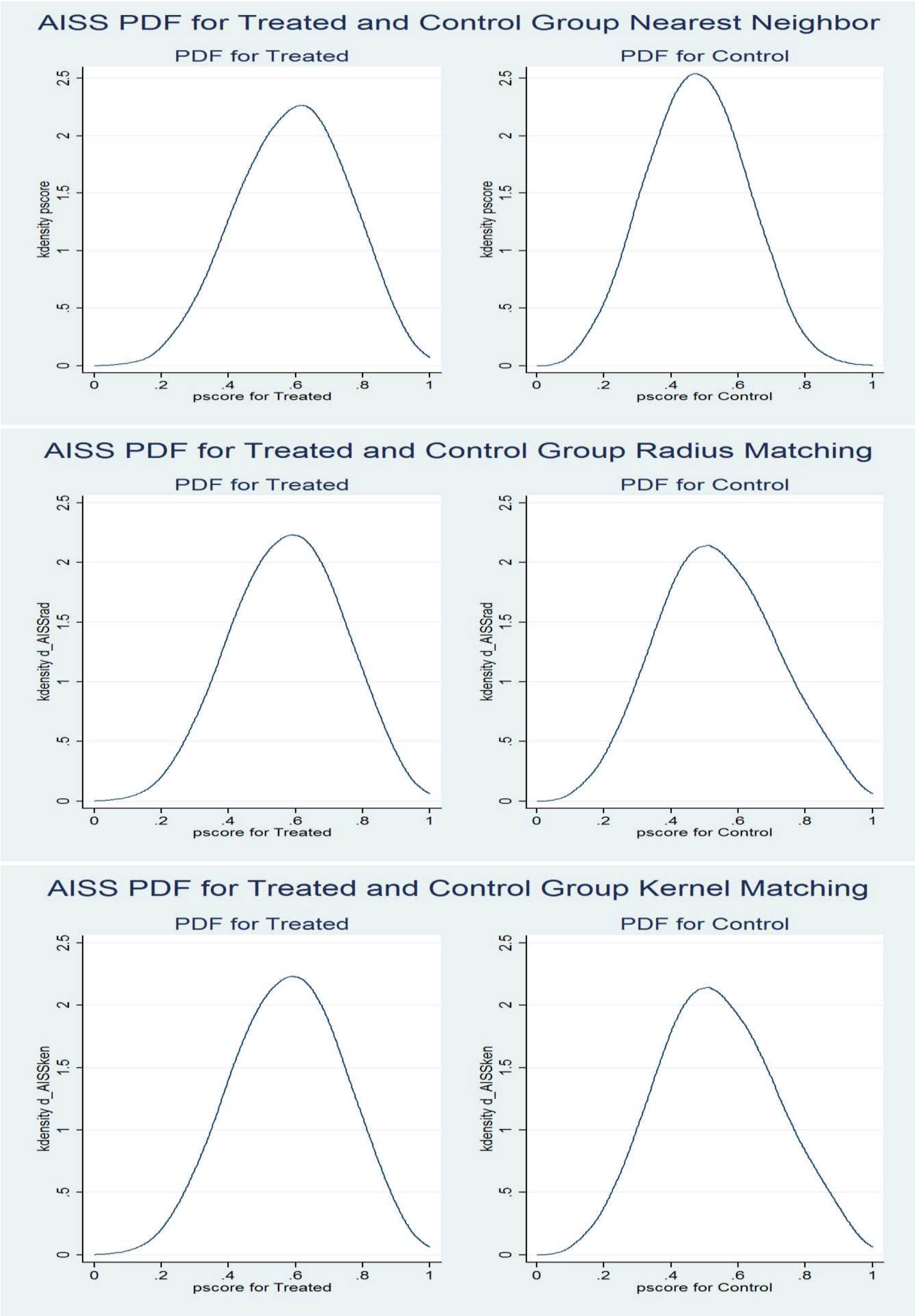


Figure 5: Model 2



Annex III: Robustness Checks

Table 3: Robustness Checks on Survey Data if Householder Resides in Rural Area

Robustness Checks	Null Hypothesis	Statistic	Model 1:	Model 2:	Conclusion
Ramsey RESET test using powers of the fitted values of dependent variable	Model has no omitted variables	F-statistic p-value	89.96 0.0000	84.17 0.0000	Reject null hypothesis. However dataset has limited observations
Functional Form and Heteroskedasticity using Cameron and Trivedi decomposition of IM-test	Heteroskedasticity Skewness Kurtosis	p-value p-value p-value	0.0000 0.0000 1.0000	0.0000 0.0000 1.0000	Reject but not for kurtosis. For skewness transform dependent variable to log form
Breusch-Pagan/Cook-Welsberg test for heteroskedasticity	constant variance	chi2 p-value	9244.36 0.0000	4086.77 0.0000	Reject & report Huber/White het-consistent standard errors: weighted least squares
Test for Multicollinearity using Variance Inflation Factors	No Multicollinearity	mean VIF	20.01	4.56	Drop some variables in both models and form principal components
Test for Endogeneity	Variables are exogenous	Robust Score chi2 p-value	7.72236 0.0055	14.3377 0.0002	reject null hypothesis and variables are endogenous
Test of Linear Hypothesis	Variables are exogenous (elderly)	F-statistic p-value	0.38 0.5400	0.01 0.9032	Instrumental variable is exogenous

Table 4: Correlation Coefficients to Determine Instrumental Variable for Household Age (Reside=Rural)

Model 1	hhage	elderly	madult	fadult	Model 2	hhage	elderly	madult	fadult
hhage	1.0000				hhage	1.0000			
elderly	0.6395	1.0000			elderly	0.5405	1.0000		
	0.0000					0.0000			
madult	-0.0583	-0.2266	1.0000		madult	-0.0382	-0.2371	1.0000	
	0.0000	0.0000				0.0388	0.0000		
fadult	0.0037	-0.2014	0.2413	1.0000	fadult	-0.0119	-0.2200	0.2288	1.0000
	0.7169	0.0000	0.0000			0.5204	0.0000	0.0000	

Annex IV: OLS Estimates of Household Model (Dependent Variable: Annual Household real expenditure per Capita)

Table 5: Regression Results on Model 1 with ATT[5] if Householder Resides in Rural Area

Model 1	IV Estimation lrexppc	rexppc	ATTND lrexppc	rexppc	ATTR lrexppc	rexppc	ATTK lrexppc	rexppc	ATTS lrexppc	rexppc
TIP	***-0.0819***	***-1399***	***-0.087***	***-1488***	***-0.071***	***-1228***	***-0.076***	***-1303***	***-0.143***	***-2521***
	(0.00)***		***(0.00)******		***(0.00)******		***(0.00)******		***(0.00)******	
agext	-0.1423		0.3016		0.3016		0.3016			
	(0.00)***		(0.00)***		(0.00)***		(0.00)***			
agextcp	-0.0705		0.2891		0.2891		0.2891			
	(0.26)		(0.19)		(0.19)		(0.19)			
agextsv	0.0152		0.1302		0.1302		0.1302			
	(0.76)		(0.55)		(0.55)		(0.55)			
agextfu	0.0619		0.2018		0.2018		0.2018			
	(0.36)		(0.36)		(0.36)		(0.36)			
agextirri	-0.0274		0.3917		0.3917		0.3917			
	(0.46)		(0.02)*		(0.02)*		(0.02)*			
agextac	0.0349		-0.1042		-0.1042		-0.1042			
	(0.38)		(0.55)		(0.55)		(0.55)			
agextmkt	-0.0250		-0.0768		-0.0768		-0.0768			
	(0.55)		(0.66)		(0.66)		(0.66)			
agextcre	0.0257		-0.0268		-0.0268		-0.0268			
	(0.53)		(0.87)		(0.87)		(0.87)			
p_tobauction	0.0003		0.0068		0.0068		0.0068			
	(0.93)		(0.45)		(0.45)		(0.45)			
p_maize	0.0119		0.0794		0.0794		0.0794			
	(0.16)		(0.00)***		(0.00)***		(0.00)***			
p_fert	0.0129		-0.0133		-0.0133		-0.0133			
	(0.00)**		(0.17)		(0.17)		(0.17)			
p_ganyu	-0.0023		-0.0945		-0.0945		-0.0945			
	(0.84)		(0.00)***		(0.00)***		(0.00)***			
p_index	0.0010		-0.0352		-0.0352		-0.0352			
	(0.91)		(0.10)		(0.10)		(0.10)			
p_char	0.0041		-0.0033		-0.0033		-0.0033			
	(0.00)***		(0.19)		(0.19)		(0.19)			
p_ker	-0.0022		0.0679		0.0679		0.0679			
	(0.85)		(0.03)*		(0.03)*		(0.03)*			
p_tpt	0.0013		-0.0137		-0.0137		-0.0137			
	(0.41)		(0.00)***		(0.00)***		(0.00)***			
p_mflour	-0.0151		0.1310		0.1310		0.1310			

[5] Second column presents results based on instrumental variable or 2SLS using complex survey design. Columns 4-10 presents Average Treatment Effects on the Treated (ATT) using propensity scores – 4th column: ATT (Nearest Neighbor matching); 6th Column: ATT (Radius matching); 8th Column: ATT (Kernel matching); 10th Column: ATT (Stratification matching)

	IV Estimation		ATTND		ATTR		ATTK		ATTS	
Model 1	lrexppc	rexppc	lrexppc	rexppc	lrexppc	rexppc	lrexppc	rexppc	lrexppc	rexppc
	(0.61)		(0.06)		(0.06)		(0.06)			
p_dwage	0.0024		0.0324		0.0324		0.0324			
	(0.65)		(0.01)**		(0.01)**		(0.01)**			
hhageiv	-0.0040		0.0272		0.0272		0.0272			
	(0.00)***		(0.00)***		(0.00)***		(0.00)***			
fadult	-0.1779		0.2257		0.2257		0.2257			
	(0.00)***		(0.00)***		(0.00)***		(0.00)***			
madult	-0.0548		0.1471		0.1471		0.1471			
	(0.00)***		(0.00)***		(0.00)***		(0.00)***			
mlgtp	0.1043		0.1289		0.1289		0.1289			
	(0.00)***		(0.13)		(0.13)		(0.13)			
mlgte	0.6322		-1.5507		-1.5507		-1.5507			
	(0.00)***		(0.00)***		(0.00)***		(0.00)***			
mcooke	0.4879		0.3412		0.3412		0.3412			
	(0.00)***		(0.60)		(0.60)		(0.60)			
mcookf	0.1014		0.0890		0.0890		0.0890			
	(0.12)		(0.68)		(0.68)		(0.68)			
mcookc	0.6286		-0.7236		-0.7236		-0.7236			
	(0.00)***		(0.06)		(0.06)		(0.06)			
fhh	0.0300		0.2815		0.2815		0.2815			
	(0.14)		(0.00)***		(0.00)***		(0.00)***			
yrsed	0.0269		-0.0579		-0.0579		-0.0579			
	(0.00)***		(0.00)***		(0.00)***		(0.00)***			
inter	0.0073		-0.0280		-0.0280		-0.0280			
	(0.10)		(0.11)		(0.11)		(0.11)			
illness	0.0565		0.1426		0.1426		0.1426			
	(0.00)***		(0.01)**		(0.01)**		(0.01)**			
farmszpc	0.5498		0.4367		0.4367		0.4367			
	(0.00)***		(0.00)***		(0.00)***		(0.00)***			
l_index	0.0218		-0.0506		-0.0506		-0.0506			
	(0.00)***		(0.01)**		(0.01)**		(0.01)**			
water	0.2176		-0.2552		-0.2552		-0.2552			
	(0.00)***		(0.04)*		(0.04)*		(0.04)*			
wbeing	0.1507		-0.0005		-0.0005		-0.0005			
	(0.00)***		(0.99)		(0.99)		(0.99)			
distmkt	***-0.0022***		0.0050		0.0050		0.0050			
	(0.03)*		(0.04)*		(0.04)*		(0.04)*			
roadbin1	0.0351		-0.0652		-0.0652		-0.0652			
	(0.36)		(0.50)		(0.50)		(0.50)			
agcredit	0.1093		-0.1532		-0.1532		-0.1532			
	(0.00)**		(0.08)		(0.08)		(0.08)			
coop	0.0004		0.1856		0.1856		0.1856			
	(0.99)		(0.09)		(0.09)		(0.09)			
irriscm	-0.0525		-0.1567		-0.1567		-0.1567			

Model 1	IV Estimation lrexppc	rexppc	ATTND lrexppc	rexppc	ATTR lrexppc	rexppc	ATTK lrexppc	rexppc	ATTS lrexppc	rexppc
	(0.23)		(0.22)		(0.22)		(0.22)			
mktsmall	-0.0203		-0.0583		-0.0583		-0.0583			
	(0.44)		(0.43)		(0.43)		(0.43)			
mktlarge	***-0.1218***		0.3662		0.3662		0.3662			
	(0.00)**		(0.00)***		(0.00)***		(0.00)***			
rain_l	-0.0546		0.2428		0.2428		0.2428			
	(0.09)		(0.00)***		(0.00)***		(0.00)***			
rain_m	0.0397		0.0330		0.0330		0.0330			
	(0.26)		(0.64)		(0.64)		(0.64)			
season1	-0.1726		-0.0494		-0.0494		-0.0494			
	(0.00)***		(0.58)		(0.58)		(0.58)			
season2	-0.1123		0.0893		0.0893		0.0893			
	(0.00)***		(0.21)		(0.21)		(0.21)			
season4	-0.1361		-0.1119		-0.1119		-0.1119			
	(0.00)***		(0.10)		(0.10)		(0.10)			
year2004	0.1545		0.1185		0.1185		0.1185			
	(0.00)***		(0.12)		(0.12)		(0.12)			
_cons	8.3034		3.2734		3.2734		3.2734			
	(0.00)***		(0.16)		(0.16)		(0.16)			
N	***7890***		***7890***		***7890***		***7890***		***9573***	
R-sq	***0.325***		***0.072***		***0.072***		***0.072***			

Marginal Effects; t-statistics in parenthesis

(d) for discrete change of dummy variable from 0 to 1

="* p<0.05 ** p<0.01 *** p<0.001"

Table 6: Regression Results on Model 2 with ATT[6] if Householder Resides in Rural Area

	IV Estimation		ATTND		ATTR		ATTK		ATTS	
Model 2	lrexppc	rexppc	lrexppc	rexppc	lrexppc	rexppc	lrexppc	rexppc	lrexppc	rexppc
aissf	***0.0821***	***1679***	***0.078***	***1605***	***0.075***	***1567***	***0.083***	***1705***	***0.073***	***1587***
	(0.02)*		***(0.07)***		***(0.30)***		***(0.01)*****		***(0.02)****	
agextsv	-0.1424		0.6203		0.6203		0.6203			
	(0.24)		(0.21)		(0.21)		(0.21)			
agextfu	0.2010		-0.6444		-0.6444		-0.6444			
	(0.11)		(0.20)		(0.20)		(0.20)			
p_lmaize	-0.0055		0.0656		0.0656		0.0656			
	(0.65)		(0.03)*		(0.03)*		(0.03)*			
p_hmaize	0.0170		-0.1011		-0.1011		-0.1011			
	(0.46)		(0.10)		(0.10)		(0.10)			
p_tobacco	0.0041		-0.0157		-0.0157		-0.0157			
	(0.15)		(0.02)*		(0.02)*		(0.02)*			
p_wage	0.0012		0.0144		0.0144		0.0144			
	(0.52)		(0.00)**		(0.00)**		(0.00)**			
hhageiv	-0.0033		0.0084		0.0084		0.0084			
	(0.08)		(0.27)		(0.27)		(0.27)			
madult	-0.0626		0.1876		0.1876		0.1876			
	(0.00)**		(0.02)*		(0.02)*		(0.02)*			
fadult	-0.1469		0.2184		0.2184		0.2184			
	(0.00)***		(0.03)*		(0.03)*		(0.03)*			
mlgtp	0.1631		0.3053		0.3053		0.3053			
	(0.01)*		(0.21)		(0.21)		(0.21)			
mlgte	1.0610		0.8316		0.8316		0.8316			
	(0.00)***		(0.40)		(0.40)		(0.40)			
mcooke	-0.0803		-1.2166		-1.2166		-1.2166			
	(0.75)		(0.37)		(0.37)		(0.37)			
mcookf	-0.0885		-0.2248		-0.2248		-0.2248			
	(0.59)		(0.73)		(0.73)		(0.73)			
mcookc	0.1420									
	(0.52)									
fhh	0.0372		-0.3711		-0.3711		-0.3711			
	(0.28)		(0.02)*		(0.02)*		(0.02)*			
consyr	-0.0139		-0.2343		-0.2343		-0.2343			
	(0.67)		(0.09)		(0.09)		(0.09)			
l_index	0.0316		0.1717		0.1717		0.1717			
	(0.09)		(0.02)*		(0.02)*		(0.02)*			
water	0.0673		0.1215		0.1215		0.1215			
	(0.60)		(0.70)		(0.70)		(0.70)			
distmkt	***-0.0019***		-0.0023		-0.0023		-0.0023			
	(0.35)		(0.71)		(0.71)		(0.71)			
mktsmall	0.0694		0.0143		0.0143		0.0143			

[6] Note that those in parenthesis for ATT are t-statistics.

	IV Estimation		ATTND		ATTR		ATTK		ATTS	
Model 2	**lrexppc**	**rexppc**	**lrexppc**	**rexppc**	**lrexppc**	**rexppc**	**lrexppc**	**rexppc**	**lrexppc**	**rexppc**
	(0.23)		(0.93)		(0.93)		(0.93)			
mktlarge	***-0.1542***		0.2436		0.2436		0.2436			
	(0.04)*		(0.20)		(0.20)		(0.20)			
roadbin1	0.1006		-0.3673		-0.3673		-0.3673			
	(0.38)		(0.26)		(0.26)		(0.26)			
roadbin3	***-0.1629***		-0.5443		-0.5443		-0.5443			
	(0.03)*		(0.02)*		(0.02)*		(0.02)*			
roadbin4	-0.1153		0.1951		0.1951		0.1951			
	(0.23)		(0.49)		(0.49)		(0.49)			
ADMARC	-0.0602		-0.2030		-0.2030		-0.2030			
	(0.40)		(0.34)		(0.34)		(0.34)			
farmszpc	0.5796		0.1514		0.1514		0.1514			
	(0.00)***		(0.51)		(0.51)		(0.51)			
wbeing	-0.0640		-0.1661		-0.1661		-0.1661			
	(0.10)		(0.32)		(0.32)		(0.32)			
poor	-0.0832		-0.5602		-0.5602		-0.5602			
	(0.03)*		(0.00)***		(0.00)***		(0.00)***			
coop	-0.0100		0.5246		0.5246		0.5246			
	(0.88)		(0.01)**		(0.01)**		(0.01)**			
irriscm	-0.1202		-0.3664		-0.3664		-0.3664			
	(0.13)		(0.06)		(0.06)		(0.06)			
ICT	-0.0698		-0.8016		-0.8016		-0.8016			
	(0.64)		(0.43)		(0.43)		(0.43)			
_cons	9.3445		-0.1758		-0.1758		-0.1758			
	(0.00)***		(0.91)		(0.91)		(0.91)			
N	***1147***	***N***	***1143***		***1143***		***1143***		***1176***	
R-sq	***0.270***	***pR-sq***	***0.066***		***0.066***		***0.066***			

Marginal Effects; t-statistics in parenthesis

(d) for discrete change of dummy variable from 0 to 1

="* p<0.05 ** p<0.01 *** p<0.001"

Annex V: ATT and Bootstrapped Standard Errors

Table 7: ATT and Bootstrapped Standard Errors for Model 1 based on IHS2 Dataset

ATTND

ATT estimation with Nearest Neighbor Matching method (random draw version)

Bootstrapped Standard Errors

	Mean	Abs. Mean	Observations	Std. Error	t-Statistic	p-value
Matched Treated	9.705	16397	4748			
Matched Controls	9.792	17885	1903			
ATT (y_1-y_0)	**-0.087**	**-1488**	**6651**	**0.021**	**-4.244**	**0.000**

Note: the numbers of treated and controls refer to actual nearest neigbor matches

ATTR

ATT estimation with the Radius Matching method

Bootstrapped Standard Errors

No. Treated	Mean	Abs. Mean	Observations	Std. Error	t-Statistic	p-value
Matched Treated	9.726	16752	2961			
Matched Controls	9.797	17980	2281			
ATT (y_1-y_0)	**-0.071**	**-1228**	**5242**	**0.024**	**-2.971**	**0.000**

Note: the numbers of treated and controls refer to actual matches within radius

ATTK

ATT estimation with the Kernel Matching method

Bootstrapped Standard Errors

No. Treated	ATT	Abs. Mean	Observations	Std. Error	t-Statistic	p-value
Matched Treated	9.705	16397	4748			
Matched Controls	9.781	17700	3139			
ATT (y_1-y_0)	**-0.076**	**-1303**	**7887**	**0.013**	**-6.027**	**0.000**

ATTS

ATT estimation with the Stratification Matching method

Bootstrapped Standard Errors

No. Treated	ATT	Abs. Mean	Observations	Std. Error	t-Statistic	p-value
Matched Treated	9.705	16397	5754			
Matched Controls	9.848	18918	3814			
ATT (y_1-y_0)	**-0.143**	**-2521**	**9568**	**0.014**	**-10.601**	**0.000**

IV Estimation

No. Treated	ATT	Abs. Mean	Observations	Std. Error	t-Statistic	p-value
Treated	9.705	16397	687			
Untreated	9.787	17796	518			
y_1-y_0	**-0.082**	**-1399**	**1205**	**0.016**	**-5.030**	**0.000**

Table 8: ATT and Bootstrapped Standard Errors for Model 2 using AISS Dataset

ATTND

ATT estimation with Nearest Neighbor Matching method (random draw version)

Bootstrapped Standard Errors

	Mean	Abs. Mean	Observations	Std. Error	t-Statistic	p-value
Matched Treated	9.966	21297	651			
Matched Controls	9.888	19692	272			
ATT (y_1-y_0)	**0.078**	**1605**	**923**	**0.052**	**1.498**	**0.0672**

Note: the numbers of treated and controls refer to actual nearest neigbor matches

ATTR

ATT estimation with the Radius Matching method

Bootstrapped Standard Errors

No. Treated	Mean	Abs. Mean	Observations	Std. Error	t-Statistic	p-value
Matched Treated	9.979	21575	106			
Matched Controls	9.904	20008	102			
ATT (y_1-y_0)	**0.075**	**1567**	**208**	**0.151**	**0.499**	**0.3092**

Note: the numbers of treated and controls refer to actual matches within radius

ATTK

ATT estimation with the Kernel Matching method

Bootstrapped Standard Errors

No. Treated	ATT	Abs. Mean	Observations	Std. Error	t-Statistic	p-value
Matched Treated	9.966	21297	651			
Matched Controls	9.883	19592	491			
ATT (y_1-y_0)	**0.083**	**1705**	**1142**	**0.032**	**2.589**	**0.0049**

ATTS

ATT estimation with the Stratification Matching method

Bootstrapped Standard Errors

No. Treated	ATT	Abs. Mean	Observations	Std. Error	t-Statistic	p-value
Matched Treated	9.966	21297	672			
Matched Controls	9.889	19709	494			
ATT (y_1-y_0)	**0.077**	**1587**	**1166**	**0.036**	**2.159**	**0.0155**

IV Estimation

No. Treated	ATT	Abs. Mean	Observations	Std. Error	t-Statistic	p-value
Treated	9.966	21297	687			
Untreated	9.884	19618	518			
y_1-y_0	**0.082**	**1679**	**1205**	**0.002**	**2.460**	**0.02**

Annex VI: Blocks/Cells for Treated and Control Groups

Table 9: Inferior Bound, Number of Treated and Controls for Each Block (Reside==Rural)

Model 1

Inferior of block of pscore	Householder received a Starter Pack (TIP) as safety net from Government		
	No	Yes	Total
0.4	58	33	91
0.45	167	108	275
0.4625	256	205	461
0.475	535	504	1039
0.5	883	1040	1923
0.55	338	394	732
0.575	287	435	722
0.6	404	678	1082
0.65	231	435	666
0.675	154	399	553
0.7	238	699	937
0.75	114	286	400
0.775	60	243	303
0.8	79	259	338
0.85	10	36	46
Total	**3,814**	**5,754**	**9,568**

Note: the common support option has been selected

Model 2

Inferior of block of pscore	Householder received both basal and top dressing subsidy fertilizers		
	No	Yes	Total
0.325	5	1	6
0.3375	8	13	21
0.35	32	16	48
0.4	36	27	63
0.45	67	64	131
0.5	79	79	158
0.55	1	5	6
0.6	248	436	684
0.65	18	31	49
Total	**494**	**672**	**1,166**

Note: the common support option has been selected

Annex VII: Data Description and Sources

Data has been obtained from two surveys in Malawi conducted by the National Statistical Office, Zomba. These include the Second Integrated Household Survey (IHS2) conducted in 2004/05 and a follow-up survey conducted in May 2007. The following is a description of the data used in the study:

Table 10: Data Description for Variables Used

Variable Name	Variable Label	Binary
rexppc	Annual Household real expenditure	
lrexppc	Natural log of Annual Household real expenditure	
TIP	Householder Received a Starter Pack (TIP) as safety net from Government	yes
agext	Field Assistant resides in Community	yes
agextcp	Householder receives advice from field assistant on general crop production	yes
agextsv	Householder receives advice from field assistant on new seed varieties	yes
agextfu	Householder receives advice from field assistant on fertiliser use	yes
agextirri	Householder receives advice from field assistant on irrigation	yes
agextac	Householder receives advice from field assistant on general animal care	yes
agextmkt	Householder receives advice from field assistant on marketing/crop sales	yes
agextcre	Householder receives advice from field assistant on access to credit	yes
p_tobauction	Average price of tobacco in district at auction floors MK/kg	
p_maize	Average price of maize in district MK/kg	
p_fert	Average price of fertiliser in district MK/kg	
p_ganyu	Average hire price of ganyu labor in district MK/day	
p_index	Average price index of miscellaneous consumables	
p_char	Average price of charcoal in district	
p_ker	Average price of kerosene in district	
p_tpt	Average price of transport in district	
p_mflour	Average price of maize flour in district MK/kg	
p_dwage	Average price of casual/ganyu labor in district MK/day	
hhage	Age of Household Head	
fadult	HH: Females 15-64 years of age	
madult	HH: Males 15-64 years of age	
mlgtp	Householder uses paraffin for lighting fuel	yes
mlgte	Householder uses electricity for lighting	yes
mcooke	Householder uses electricity for cooking	yes
mcookf	Householder uses firewood for cooking	yes
mcookc	Householder uses charcoal for cooking	yes
fhh	Householder is female (0/1)	yes
yrsed	years of education	
inter	Interaction term between fhh and yrsed	
elderly	H: Individuals 65+ years of age	
illness	Householder or wife had a serious illness that prevented participation in activities	yes
farmszpc	Total land holding per person	
l_index	Livestock index based on principal components analysis	
water	Householder has access to personal water supply	yes
wbeing	Householder considers wellbeing in year improved 0/1	yes

Variable Name	Variable Label	Binary
distmkt	distance (km) to nearest daily market	
reside	Urban/Rural dummy	yes
roadbin1	road==Tar/Asphalt Graded	yes
roadbin3	road==Dirt Road (maintained)	yes
roadbin4	road==Dirt track	yes
agcredit	Existence of Farmers credit clubs in community	yes
coop	Existence of Farmers cooperatives in community	yes
irriscm	Irrigation scheme in community	yes
mktsmall	Access to a Daily Market in community	yes
mktlarge	Access to a Larger Market in community	yes
rain_l	For growing maize, the amount of rain was too little	yes
rain_m	For growing maize, the amount of rain was too much	yes
season1	Interview took place in the months of Dec, Jan, Feb	yes
season2	Interview took place in the months of March, April, May	yes
season4	Interview took place in the months of Sept, Oct, Nov	yes
year2004	Interview took place in 2004	yes
psu	Enumeration Area/PSU (564 total)	
hhwght	IHS2 HH weight	
hhsize	HH Size (based on household members	
strata	Stratum: district & urban/rural (30 total)	
aissf	Householder received both basal and top dressing subsidy fertilizer in 2006/07	yes
p_lmaize	Average price of local maize in district MK/kg in 2006/07	
p_hmaize	Average price of hybrid maize in district MK/kg in 2006/07	
p_tobacco	Average price of burley tobacco in district MK/kg in 2006/07	
p_wage	Average wage of casual/ganyu labour in district MK/day in 2006/07	
consyr	Householder considers food consumption inadequate in 2006/07	yes