Estimating the causal effect of improved fallows on farmer welfare using robust identification strategies in Chongwe - Zambia

Elias Kuntashula
University of Pretoria
Department of Agricultural Economics, Extension and Rural Development,
Pretoria 0002, South Africa.

ekuntashula@unza.zm,

Tel: +260 977 748335

Eric Mungatana
Department of Agricultural Economics, Extension and Rural Development, University of Pretoria.
Pretoria 0002, South Africa.

eric.mungatana@up.ac.za

Tel: +270 785238127

ABSTRACT

Agricultural technological improvements are crucial to increase on farm production and thereby reduce poverty. However the use of improper identification strategies on the impacts of improved technologies on farmer welfare could potentially pose a threat to good practice agricultural policy making. In this paper, propensity matching strategies and endogenous switching regression were used to test whether an improved fallow, a soil fertility improving technology that passed the requirements for a high impact intervention based on non randomised impact assessment methodologies could still pass this test. Using data from 324 randomly surveyed households in Chongwe district of Zambia, the rigorous econometric methods confirmed the positive impact of improved fallows on household maize yields, maize productivity, per capita maize yield and maize income. Conflicting results were obtained when a broader welfare indicator – per capita crop income, was considered. Whereas the non-randomised and kernel matching methods showed that per capita crop incomes were significantly higher for the adopters than for the non adopters, the causal effect of improved fallows on this variable was non significant when nearest neighbour matching strategy and the more robust endogenous switching regression were used. It was concluded that the technology improves welfare through increased maize and hence increased food security, and through incomes from the maize crop. The maize income derived from improved fallows were however not sufficient enough to drive the general crop income to significantly higher

levels. The need to diversify the use of improved fallows on high valued crops was recommended while the importance of using better and more robust methodologies in evaluating impact of interventions was emphasised.

Key words: Confounding factors, Identification strategy, selection bias

1. INTRODUCTION

Soil fertility problems are widely spread throughout sub-Saharan Africa. Several studies (Sanchez and Jama, 2002; Vanlauwe and Giller, 2006) have noted that a fundamental impediment to agricultural growth and a major negative social externality in sub-Saharan Africa is declining soil fertility and low macro-nutrient levels. In the past, the region's small scale farmers who could not afford inorganic fertilisers used traditional methods of farming such as shifting cultivation in order to sustain land productivity. However, the decrease in high potential land and the increase in human population have added pressure to farming extending into more fragile lands, thus undermining the soil resource capital base (Ajayi et al. 2007).

In an effort to contribute towards bridging the gap posed by soil fertility problems, limited use of external inputs and acute poverty among small scale farmers, the improved fallow technology was developed for use in Zambia and elsewhere in sub-Saharan Africa (Mafongoya et al. 2006). The improved fallow, an ecologically robust approach to soil fertility improvement, is a product of many years of agroforestry research and development by the World Agroforestry Centre (WAC). The technology is composed of fast growing mostly nitrogen fixing trees of *Fhaiderbia albida Sesbania sesban*, *Gliricidia sepium*, *Teprosia vogelii* and *Cajanus cajan*, that ensure the shortest soil regeneration period of 2 to 3 years. Farmers can grow their crop on previously improved fallow plots for the next 3 to 4 years without applying any external inputs. The technology also enhances environmental quality through the generation of several ecosystem services such as carbon sequestration (Makumba et al. 2007), conservation of biodiversity (Sileshi et al. 2007), protection of natural forests by providing an alternative source of fuel wood supply, and prevention of soil erosion (Mafongoya and Kuntashula, 2005).

The financial profitability of improved fallows in Zambia and sub-Saharan Africa has been demonstrated by several studies including those conducted by Ajayi et al. (2007), Ajayi et al.

(2009), Franzel (2004) and Place et al. (2002). These studies demonstrate that improved fallows are more profitable than the non-use of any external inputs, a practise prevalent among resource poor farmers (Mafongoya et al. 2006). Several studies (Akinnifesi et al. 2006; Ajayi et al. 2007, Phiri et al. 2004; Quinion et al. 2010) also indicate that farmers who take up the technology have higher welfare, measured in terms of outcome parameters such as increased maize yields, household incomes, and assets among others. Despite all these demonstrated benefits, only a few resource constrained farmers have taken up the technology (Akinnifesi et al. 2006; Ajayi et al. 2007).

A critical literature review of the methodologies used to estimate welfare impact in the above cited studies show that they failed to move beyond estimating incremental maize yields, crop incomes and assets that adopters supposedly gain. For instance in the study done in Zambia, Ajayi et al (2007) used two indicators: farmer perceptions of yields and number of months per year when the household had enough food to feed family members, to measure impact. The study's findings were that the technology positively impacts on welfare. When analysing the number of months per year when households have enough food, the study only controlled for household size. However, including the number of months the household has enough food without necessarily controlling for other variables may produce misleading estimates about causality. Both biophysical variables as well as socioeconomic characteristics of farmers could be important in so far as increasing the availability of food on-farm is concerned.

Franzel, (2004) and Ajayi et al. (2009) used enterprise budgets through farm modelling to assess the impact of adopting improved fallows in Zambia. The technology was found to have a positive effect on household annual maize incomes. These studies used net present value and cost benefit ratio criteria to arrive at this conclusion. While these criteria are indeed important and beneficial in estimating profitability, they fail short of measuring causality since covariates that equally would have led to an increase in maize yields (hence maize income) were not controlled for. A more recent and detailed study on agroforestry and improvement in resource poor farmers' livelihoods was conducted in Malawi by Quinion et al. (2010). The study used sign and signed rank non-parametric analysis to test for a change in crop yield and asset variables between pre- and post-adoption. These tests were complemented with a test for equality of proportions to examine the probability of an increase in income, the number and type of income sources, and maize yield as a result of adopting agroforestry. While this study analysed the effects of agroforestry on poverty reduction in far more details than the earlier ones, it specifically notes that the methodologies used are based on analysing pre- and post-adoption only. The control of other factors in influencing welfare changes was not considered. We can thus conclude from the above studies on welfare impact estimation of improved fallows that they did not follow proper identification strategies in isolating the causal effect of the technology. Several biophysical as well as socioeconomic factors (including unobservable factors) that could equally have an influence on farmer welfare were never controlled for.

The purpose of this study was to estimate the impact of improved fallows on farmer welfare using more robust cause effects identification strategies. The above literature review clearly shows that the technology is not only affordable to resource constrained farmers but also improves their welfare, which leads to a number of questions: why are resource constrained farmers not adopting it in the interest of maximizing private profits as economic theory would predict? In measuring impact, have economists been measuring the right construct? Assuming economists have been measuring the right construct, are they doing the measurement correctly? It is our contention that when it comes to impact evaluation, approaches that do not encompass more robust identification strategies of the treatment technology on the outcome variables could produce misleading cause-effect estimates. Over or under estimation of impact could occur if a clear identification strategy is not used. It is well recognized that the estimate of a causal effect obtained by comparing a treatment group with a non-experimental group could be biased because of selection bias problems (Dehejia and Wahba, 2002). There could have been selection bias in the assignment of farmers taking up the improved fallow technology. Over time, selection bias could have manifested in the difference in average outcome or welfare between those who adopted and those who did not adopt regardless of the effect of the technology. Angrist and Pischke (2009) noted that the selection bias could be so large in absolute terms that it completely masks a treatment effect. It follows that to attribute a technology as causing impact, selection bias has to be overcome. This is the goal of most empirical economic research (Angrist and Pischke 2009).

We used farm-level data collected in 2011 from a random cross-section sample of 324 small-scale farmers in Zambia to estimate the impact of improved fallows. Since the improved fallow is mainly used to promote maize production, the staple food in most parts of Southern Africa, welfare indicators used in this study included household total maize yield, per capita maize yield, maize productivity and per capita income emanating from the maize crop. In addition, we included income from all crops grown on the farm to assess the technology's impact on this broad variable. The econometric methods' estimates confirmed the positive impact of improved fallows on the chosen welfare parameters. However, conflicting evidence was obtained on whether the technology positively affects per capita crop income.

Our main contribution in this paper is to demonstrate the likelihood that the earlier studies evaluating the impact of improved fallows on farmer welfare might not have succeeded in analyzing adopters and non-adopters that were similar in terms of the distribution of covariates. Stated otherwise, the earlier studies could have analyzed observations that were not necessarily comparable, possibly leading to biased conclusions concerning impacts of the technology (Heckman et al. 1998). We base this conclusion on the fact that as opposed to earlier studies, in this study we controlled for selection bias through matching strategies, and endogeneity bias that may potentially arise due to correlation of the unobserved heterogeneity and observed explanatory variables through use of endogenous switching regression model. In addition, to improve on the quality of parameter estimates, only observations that were matched during the matching analysis stage were used in the switching regression model.

The paper is structured as follows: theoretical frameworks on propensity matching and endogenous switching regression immediately follow this introduction section. Discussions on the study area, sampling design, survey instrument development and implementation, analysis and computational methods in this order, complete the section on methodology. Immediately after the survey implementation section, the paper gives the results that are discussed in the subsequent section. Finally conclusions are drawn based on the findings of the study.

2. THEORETICAL FRAMEWORKS AND METHODS

2.1 Framework for propensity score matching

The potential outcome framework for causal inference discussed by Rubin (1974) estimates the Average Treatment effect on the Treated (ATT) or adopters of improved fallows as:

$$E(Y_1 - Y_0 \backslash T = 1) \quad (1)$$

where E is the expectation in the difference in the outcome $(Y_1 - Y_0)$ between receiving treatment or adopting, T =1 and the counter factual outcome if treatment or the technology had not been received T = 0. One possible identification strategy is to impose the Conditional Independent Assumption (CIA) that states that, given a set of observable covariates X, the potential outcome in case of no treatment or not adopting is independent of treatment or technology assignment:

$$Y_0 \perp\!\!\!\perp T \backslash (X) \quad (2)$$

Besides the CIA, a further requirement for identification is the common support or overlap condition, which ensures that for each treated or adopting unit there are control or non-adopting units with the same observables (equation 5).

$$Pr(T = 1 \backslash X) < 1. \quad (3)$$

With the above two assumptions, within each cell defined by X, treatment or technology assignment is random, and the outcome of control units can be used to estimate the counter factual outcome of the treated in the case of no treatment (Nannicini, 2007).

Matching on every covariate is difficult to implement when the set of covariates is large. To overcome the curse of dimensionality, Rosenbaum and Rubin (1983) show that matching on a single index, the propensity score, rather than on a multimensional covariate vector is possible. According to Heckman et al. (1998), the propensity score is defined as the conditional probability of receiving treatment or in this case of adopting the improved fallow technology. Mathematically, the propensity score can be expressed as:

$$e(x) = \Pr(W_i^a = 1 \backslash X_i = x) = E[W_i^a \backslash X_i = x] \quad (4)$$

Where W_i =1, for treated farmers, and W_i = 0, for untreated farmers; a = improved fallow technology; and X_i is the vector of treatment covariates. The Propensity Score is usually unknown and this study estimated it through a probit regression in which the dependent variable equaled one if the household adopted improved fallows and zero otherwise. This was followed by checking the balancing properties of the propensity scores. The balancing procedure tests whether or not adopter and non-adopter observations have the same distribution of propensity scores. Various specifications of the probit model were attempted until the most complete and robust specification that satisfied the balancing tests and establishment of the common support region was obtained.

Matching was implemented using nearest neighbour with replacement and Epanechnikov kernel (bandwidth 0.06) matching techniques. For both techniques, the sample was bootstrapped 100 times. With nearest neighbour matching, the individual from the comparison group is chosen as a matching partner for a treated individual that is closest in terms of propensity score. With replacement meant that an untreated individual could be used more than once as a match. Matching with replacement increases the average quality of matching and decreases bias (Caliendo and Kopeinig, 2005).

Unlike the nearest neighbour matching algorithm that ensures only a few observations from the comparison group are used to construct the counterfactual outcome of a treated individual, Kernel matching (KM) is a non-parametric matching estimator that uses weighted averages of all individuals in the control group to construct the counterfactual outcome. KM is therefore associated with lower variance because more information is used. One drawback of this approach is the possibility of using bad matches. It is for this reason that the proper imposition of the common support condition is of major importance for KM (Caliendo and Kopeinig, 2005).

2.2 Endogenous switching model

Matching strategies only control for heterogeneity effects due to observable covariates. To account for endogeneity bias and the effects of unobservable covariates, the study employed endogenous switching regression techniques. The study specified the model for technology adoption following Loksin and Sajaia (2004). This model is comprised of the selection equation or the criterion function and two continuous regressions that describes the behaviour of the farmer as he faces the two regimes of adopting the improved fallows or not. The selection equation is defined as;

$$I_i^* = \alpha Z_i + \mu_i \qquad \text{with } I_i = \begin{cases} 1 & if\ I_i^* > 1 \\ 0 & otherwise \end{cases} \tag{5}$$

where I_i^* is the unobservable variable for technology adoption and I_i is its observable counterpart which is the dependent variable (adoption of improved fallow) which equals one, if the farmer has adopted and zero otherwise. α is a vector of parameters while Z_i are non-stochastic vectors of observed farm and non-farm characteristics determining adoption and μ_i is random disturbances associated with the adoption of improved fallows.

The two welfare regression equations where farmers face the regimes of adopting or not to adopt improved fallows are defined as follows:

Regime 1: $y_{1i} = \beta X_{1i} + \varepsilon_{1i}$ if $I_i = 1$ (6)

Regime 2: $y_{2i} = \beta X_{2i} + \varepsilon_{2i}$ if $I_i = 0$ (7)

where Y_{ji} are the dependent variables or outcome variables (such as maize yield, crop income etc) in the continuous equations; X_{1i} and X_{2i} are vectors of exogenous variables; β1 and β2 are vectors of parameters; and ε_{1i} and ε_{2i} are random disturbance terms.

The error terms are assumed to have a trivariate normal distribution with mean vector zero and covariance matrix:

$$\Omega = \begin{pmatrix} \sigma_\mu^2 & . & . \\ \sigma_{21} & \sigma_1^2 & . \\ \sigma_{31} & . & \sigma_2^2 \end{pmatrix} \tag{8}$$

where σ_μ^2 is a variance of the error term in the selection equation, and σ_1^2 and σ_2^2 are variances of the error terms in the continuous equations. σ_{21} is a covariance of μ_i and ε_{1i}. σ_{31} is a covariance of μ_i and ε_{2i}. Since Y_{1i} and Y_{2i} are never observed simultaneously the covariance between ε_{1i} and ε_{2i} is not defined. According to Asfaw (2010), an important implication of the error structure is that because the error term of the selection equation μ_i is correlated with the error terms of the welfare outcome functions ε_{1i} and ε_{2i}, the expected values of ε_{1i} and ε_{2i} conditional on the sample selection are nonzero:

$$E[\varepsilon_{1i} / I_i = 1] = \sigma_{\varepsilon 1\mu} \frac{\phi(\alpha Z_i)}{\Phi(\alpha Z_i)} = \sigma_{\varepsilon 1\mu} \lambda_{1i} \quad and \quad E[\varepsilon_{2i} / I_i = 0] = -\sigma_{\varepsilon 2\mu} \frac{\phi(\alpha Z_i)}{1 - \Phi(\alpha Z_i)} = \sigma_{\varepsilon 2\mu} \lambda_{2i} \quad (9)$$

Where $\phi(.)$ is the standard normal probability density function, $\Phi(.)$ the standard normal cumulative function, $\lambda_{1i} = \frac{\phi(\alpha Z_i)}{\Phi(\alpha Z_i)}$, and $\lambda_{2i} = -\frac{\phi(\alpha Z_i)}{1 - \Phi(\alpha Z_i)}$. If the estimated covariances $\sigma_{\varepsilon 1\mu}$ and $\sigma_{\varepsilon 2\mu}$ are statistically significant, then the decision to adopt and the welfare outcome variables are correlated, that is we find evidence of endogenous switching and reject the null hypothesis of absence of sample selectivity bias. According to Maddala and Nelson (1975), this model is defined as 'switching regression model'.

There are several ways in which this model can be estimated. Maddala (1983) proposes a two step procedure that however requires some adjustments to derive consistent standard errors and according to Hartman (1991) and Nawata (1994) quoted in Asfaw (2010), this procedure shows poor performance in case of high multicollinearity between the covariates of the selection equation and the covariates of the welfare outcome equations. The endogenous switching regression models can efficiently be estimated using the full information maximum likelihood (FIML) estimation (Lokshin and Sajaia, 2004). The FIML method simultaneously estimates the probit criterion or selection equation and the regression equations to yield consistent standard errors. The model is identified by construction through non-linearities. Given the assumption of trivariate normal distribution for the error terms, the logarithmic likelihood function for the system of equations 5, 6, and 7 can be given as follows:

$$InL = \sum_{i=1} \{I_i w[In(\Phi(\eta_{1i}) + In(\phi(\varepsilon_{1i} / \sigma_1) / \sigma_1) + (1 - I_i) w_i [In(1 - \Phi(\eta_{2i})) + In(\phi / \varepsilon_{2i} / \sigma_2) / \sigma_2]]\} \quad (10)$$

where w_i is an optional weight for observation i and $\eta_{ji} = \frac{(\alpha Z_i + \rho_j \varepsilon_{ji} / \sigma_j)}{\sqrt{1-\rho_j^2}}$ $j = 1,2$ where

$\rho_1 = \frac{\sigma_{21}^2}{\sigma_\mu \sigma_1}$ and $\rho_2 = \frac{\sigma_{31}^2}{\sigma_\mu \sigma_2}$ are the coefficients of correlation between ε_{2i} and $\mu_{i.}$. To make sure that the estimated ρ_1, ρ_2 are bounded between -1 and 1 and estimated σ_1, σ_2 are always positive, the maximum likelihood directly estimates $In\sigma_1, In\sigma_2$ and $a\tanh\rho$:

$$a\tanh\rho = \frac{1}{2} In\left(\frac{1+\rho_j}{1-\rho_j}\right)$$

The FIML estimates of the parameters of the endogenous switching regression model can be obtained using the STATA command *movestay* proposed by Lokshin and Sajaia (2004).

2.2.1 Conditional expectations, treatment and heterogeneity effects

After estimating the model's parameters the following conditional expectations can be used to compare the various expected outcomes of the farm households:

(a) that adopted the improved fallows

$$E(y_{1i} / I_i = 1, x_{1i}) = x_{1i}\beta_1 + \sigma_{\varepsilon 1\mu}\lambda_{1i} \quad \text{(11a}$$

(b), that did not adopt the improved fallows

$$E(y_{2i} / I_i = 0, x_{2i}) = x_{2i}\beta_2 + \sigma_{\varepsilon 2\mu}\lambda_{2i} \quad \text{(11b)}$$

(c) that the adopted farm households did not adopt, and

$$E(y_{2i} / I_i = 1, x_{2i}) = x_{2i}\beta_1 + \sigma_{\varepsilon 2\mu}\lambda_{1i} \quad \text{(11c)}$$

(d) that the non-adopters farm households adopted.

$$E(y_{1i} / I_i = 0, x_{1i}) = x_{1i}\beta_2 + \sigma_{\varepsilon 1\mu}\lambda_{2i} \quad \text{(11d)}$$

Cases (a) and (b) represent the actual expectations observed in the sample while cases (c) and (d) represent the counterfactual expected outcomes. The effect of the treatment on the treated (TT) (effect of improved fallows on the adopters) is the difference between (a) and (c) while the effect of the treatment on the untreated (TU) for the farm households that actually did not adopt improved fallows is the difference between (d) and (b).

According to Asfaw (2010), heterogeneity effects due to unobservable factors such as management skills can also be estimated. These include; the difference in the expected outcomes of the adopters of improved fallows (a) and that of the non-adopters had they adopted (d). Similarly for the group of farm households that decided not to adopt, this is the difference between (c) that the adopters did not adopt and (b) the non-adopters. Finally, the difference between TT and TU can be estimated. This effect called "transitional heterogeneity" (TH), estimates whether the impact of adopting improved fallows is larger or smaller for the farm households that actually adopted the technologies or for the farm household that actually did not adopt in the counterfactual case that they did adopt.

2.3 Study area

The study was conducted in Chongwe district of Lusaka province of Zambia in November and December 2011. Agroforestry research and development in Zambia has mainly been conducted in the Eastern province with Chipata district being the main hub and in Lusaka province, with Chongwe district housing the Kasisi Agricultural Training Centre (KATC) that promotes agroforestry among its other activities. Since the scaling down of agroforestry activities by WAC in eastern Zambia in late 2000, farmer enthusiasm towards the agroforestry in Eastern Province has been on the decline. Chongwe district was purposively chosen for this case study since KATC is still very active in the area. Informal interviews specifically designed to plan for the study and to identify areas where agroforestry is most concentrated in the district were held with extension officers from KATC. Three agricultural (out of 28) camps namely Nyangwena, Chinkuli and Katoba were identified as the main catchment areas with farmers practising improved fallows. These camps were targeted for the study. The farmers in the study area are mostly subsistence who grow mainly the staple maize crop for food and the surplus for sale. The common cash crops grown in the area include groundnuts, cotton, beans and garden vegetables such as rape, cabbage, tomato and onion. The most common animals reared include cattle, chickens and goats.

2.4 Sampling

The study used agricultural camp lists compiled in consultation with Ministry of Agriculture camp extension officers to devise a sampling frame. To ensure a complete listing of the households in the study area, agricultural camp extension officers who stay with the local communities were initially requested to thoroughly go through existing lists and update accordingly if there were any households that they had omitted within their catchment areas. The resulting lists from the three camps were then consolidated into one sampling frame, which was then stratified into adopters and non-adopters of improved fallows. The sampling frame had a total of 7,081 households of which approximately 20 percent were adopters. Due to limited logistics, the study aimed at interviewing around 5 percent (335 households) from this sampling frame. Since matching strategies require treatment units to have a larger pool of control units from which matches can be obtained (Caliendo and Kopeinig, 2005), the sample was stratified into 2:3 ratios for the adopters and non-adopters respectively. Therefore from a stratum of 1,416 listed improved fallow adopting households, 134 were selected randomly using stata (Stata version 11.2, 2009). Similarly, from 5,665 listed households, 201 non-adopters of improved fallows were randomly selected using stata. Eventually, due to non-responses, 130 adopters and 194 non-adopters respectively were finally interviewed.

This study defined an adopter of improved fallows as one who has been using the technology for at least the last six years (since 2006 and before) and has been growing at least a quarter of a hectare using this technology. The minimum six year period of use criterion was meant to exclude farmers who just tested the technology with the influence of KATC but decided to abandon it after the first cycle or before they could even experience a post fallow crop. We noted in the introduction that it takes 2 -3 years for improved fallows to mature. This is followed by up to 3 rounds of post fallow cropping before the cycle starts again. It follows that it takes a minimum of 5-6 years for a farmer to reap maximum benefits from planting improved fallows. Key informant interviews with KATC officers revealed that farmers who do not adopt after testing the technology would have started using other forms of external inputs on former improved fallow plots before this five to six year full cycle is completed. Although some farmers would plant the subsequent improved fallow before the residual effect from the preceding fallow is completely exhausted, the six year minimum period would ensure that they had benefitted in terms of post fallow crop production even after the initial testing of the technology. This condition mainly knocked out the households who had improved fallows at the time of the study but had not experienced a post fallow crop (17 farmers). The criterion on area was meant to exclude households who had planted just a few improved fallow trees for ornamental purposes. Only two farmers who had just planted a few scattered improved fallow trees were affected by this condition. Therefore in total, 19 households dropped out from the adoption category. These were added to the non-adopters at the results analytical stage on grounds that whatever fallows they may have had on their farms had no impact on post-fallow crop production. As a result the final sample used in analysis was composed of 111 adopters and 213 non-adopters of improved fallows.

2.5 Survey instrument development and pre-testing

Considerable time and effort was expended in designing the survey instrument. The first author informally interviewed officers at KATC, agricultural camp extension officers and some lead farmers (defined as farmers who are the entry points to villages and work closely with agricultural extension officers in their areas) in the catchment areas. The informal interviews covered a wide range of issues including the general agricultural practices and agroforestry activities in the area. Factors affecting the farmers' up take of the improved fallows were also discussed. Using findings from these discussions and a review of literature, a structured formal questionnaire was drafted. The questionnaire went through several refinements following the interactions between the authors. The final version of the questionnaire particularly useful for this specific study covered three main sections. The first section covered the basic households' demographic and socioeconomic characteristics. The second section explored the wealth status of households and use of improved fallows. The final section assessed the general agricultural practices such as agricultural related challenges; type and amounts of inputs used and crop production levels for the different inputs including improved fallows.

We also included questions on whether the current demographic and socioeconomic characteristics, and agricultural related challenges where the same at technology adoption (for adopters) or six years before the survey period (for non adopters). This was important for assessing impact of the technology using pre-adoption covariates.

2.6 Survey implementation

Before the formal survey a pre-test study comprising 16 households was carried out in the study area. The pre-test survey served two purposes; first, the study wanted to ensure that the questionnaire had questions that were well understood by the farmers and were flowing in a logical way. Secondly, the pre-testing provided the opportunity to practically train the research assistants (who have had a day of theoretical training) on the survey implementation. Only a few modifications were made on the questionnaire after the pre-testing. The finalised questionnaire was used to interview the 324 households selected for this study. The first author, the three camp extension officers from the catchment areas and an officer from KATC were involved in both the pre-testing and final implementation of the survey.

2.7 Analysis and computational methods

We used Stata version 11.2, 2009 to randomly select the households discussed in section 2.4 and to perform several analytical procedures in estimating the impact of improved fallows. First, we analysed means and proportions for the whole sample and then compared the characteristics between adopters and non-adopters of improved fallows using the t-distribution (continuous variables) and chi-square distribution (discrete variables) at $P = 0.05$ significance level. These characteristics (and other variables) were later used as explanatory variables in the estimation of the propensity score (appendix 1), and treatment and outcome models that are presented under the matching and endogenous switching regression models. A combination of improved fallow adoption literature, economic theory and the outcome of informal meetings with KATC staff and lead farmers were helpful in selecting the explanatory variables used.

To estimate the propensity score (PS), we used probit regression in which the dependent variable equalled 1 if the household had adopted the improved fallow technology and zero otherwise. Various specifications of the probit model were attempted until the most complete and robust specification that satisfied the balancing tests was obtained. Using the estimated propensity score, the estimation of the Average Treatment effect on the Treated (ATT) on several outcome variables was implemented. As is common practise, we weighted the non- adopters propensity scores by the propensity score divided by one minus the propensity score (PS/(1-PS)). During matching we bootstrapped the sample 100 times to obtain standard errors. We then used the nearest neighbour matching (*ATTn*) and kernel matching (*ATTk*) stata commands (Stata version 11.2, 2009) to estimate the average treatment effect of the improved fallows on welfare.

To test for matching results robustness and account for unobservable selection bias, the welfare outcome variables were subjected to endogenous switching regression analyses. Switching regression was used to predict and compute welfare outcomes in the mean differences between a) adopters having adopted and had they not adopted, and b) non-adopters having not adopted and had they adopted. The differences in (a) and (b) gave the treatment effect on the treated (TT) and the treatment effect on the untreated (TU); the differences in outcome variables between the adopters and the non-adopters called base heterogeneity (BH), and the difference in TT and TU called transitional heterogeneity (TH). The computations were performed using the *movestay* command in stata (Stata version 11.2, 2009).

3. RESULTS

3.1 Descriptive statistics

The first section of results provides a description of the socioeconomic characteristics of the sample households with a special focus on the comparison between the adopters and non-adopters of improved fallows. A description of socioeconomic characteristics of the households' heads in the surveyed area is shown in Table 1. The table only shows the characteristics whose differences between the adopters and non adopters were significant. There was no significant difference in the average age of the adopters and non-adopters. Overall, the average age of the surveyed household heads was about 46.7 years. The average active family labor force was 4.6 persons for adopters and 3.8 for non-adopters and the difference was statistically significant supporting the importance of effective family labor for adoption of improved fallows. Both farm size and cropped land in 2010/2011 season were statistically higher for the adopters than the non-adopters of improved fallows.

The sample was dominated by male headed households with no distinguishable differences in gender between the adopters and non-adopters. More adopters of improved fallows were educated compared to non-adopters. About 40% of the adopters had been to secondary school compared to about 30% of the non-adopters. No significant difference was observable in the marital status of household heads. For both categories more than 80% of households were from married homesteads. Adopters had large farm sizes, cropped land as well as land put to maize production in 2010/2011 season (Table 1).

Table 1: Households socioeconomic characteristics of sample farmers in Chongwe district, Zambia[1]

	Adopters (N = 111)	Non-adopters (N = 213)	Over all (N = 324)
Household size (MEU)	4.6 (0.181)	3.8 (0.124)***	4.1 (0.104)
Farmland size (ha)	5.2 (0.279)	3.25 (0.133)***	3.90 (0.139)
Cropped land(ha)	3.4 (0.175)	2.2 (0.089)***	2.6 (0.089)
Cropped maize area (ha)	2.3 (0.132)	1.4 (0.071)***	1.7 (0.069)
Improved fallow area (ha)	0.86 (0.049)	0.04 (0.021)***	0.29 (0.028)
Education (% households heads)			
Never been to school	3.6	10.3**	8
Attended primary	23.4	35.7**	31.5
Completed secondary	11.7	3.3***	6.2
Marital status (% households)			
Divorced (= 1, otherwise = 0)	0	3.8*	2.8
Farming group membership (% households)			
(Yes = 1, otherwise =0)	96.4	66.4***	76.6

*, **, *** significant difference between adopters and non-adopters means at 90%, 95% and 99% confidence levels. Figures in parentheses are standard errors of the mean

[1] Variables showing non-significant differences between adopters and non-adopters are not included in the Table.

Man equivalent units (meu) were calculated following Runge-Metzger (1988) as: < 9years = 0; 9 to 15 and over 49 years = 0.7; 16 to 49 = 1. Using meu is important since not all household members would provide farming labour.

3.2 Adoption of improved fallows and distribution of wealth assets

Among the improved fallow technologies, pigeon pea (*Cajanus cajan*) was found to be the most popular in the study area. Seventy eight percent of the adopters had pigeon pea growing in their fields at the time of the survey. The average area under pigeon pea was 0.56ha. Thirty percent of the adopters had *Fhaiderbia albida* covering an area of 0.89 ha on average while 18.9% of the adopters had *Tephrosia vogelii* on an area of = 0.48ha. Some insignificant number of adopters (0.05%) had *Sesbania sesban* growing in their field and one household had *Gliricidia sepium*.

The adopters of improved fallows had more cattle, goats, poultry and bicycles than the non-adopters (Table 2). However, the average number of oxen, pigs, donkeys, oxen implements, sprayers, radios, television sets and iron roofed houses were not statistically different between the adopters and non-adopters of improved fallows.

Table 2: Proportions of households owning various levels of assets in Chongwe district, Zambia [1]

	Adopters (N =111)		Non-adopters (N = 213)		Over all (N = 324)	
	% households	Mean (std. error)	% households	Mean (std. error)	% households	Mean (std. error)
Cattle	56.8	11.1 (0.929)	30.0	6.9 (0.904)***	39.2	9.0 (0.673)
Goat	48.6	9.6 (0.973)	49.8	7.4 (0.654)*	49.4	8.1 (0.547)
Poultry	91.9	20.3 (1.049)	88.3	17.9 (0.925)*	89.5	18.8 (0.706)
Bicycles	82.9	1.5 (0.078)	74.2	1.3 (0.044)**	77.2	1.4 (0.041)

*, **, *** significant difference between adopters and non-adopters means at 90%, 95% and 99% confidence levels
[1] Variables showing non-significant differences between adopters and non-adopters are not included in the Table.

The adopters of improved fallows were well off in most of the outcome or welfare variables (Table 3). They had significantly higher income from crop sales and income from the staple maize crop. The adopters of improved fallows also had significantly higher maize yields than the non-adopters. The adopters also recorded a high number of months per year when they had their own home grown food. The non-adopters had significantly higher off farm income than the adopters (Table 3).

Table 3: Average differences in several outcome variables between adopters and non-adopters of improved fallows in Chongwe district, Zambia

	Adopters (N = 111)	Non-adopters (N = 213)	Mean difference	t stat[1]
Crop Income per MEU[2] (ZK, 000)	888 (99)	366 (51)	522 (112)	4.670
Maize Income per MEU (ZK, 000)	811 (96)	279 (44)	532 (105)	5.055
Off farm Income[3] per MEU (ZK,000)	247 (43)	470 (49)	-223 (65)	-3.446
Total Maize yield (ton)	4.61 (0.302)	2.10 (0.150)	2.52 (0.337)	7.488
Maize yield (ton/ha)	2.21 (0.119)	1.50 (0.070)	0.72 (0.138)	5.175
Months per year with enough grown food	10.9 (0.145)	9.8 (0.136)	1.10 (0.199)	5.519

[1]Equal variance not assumed, figures in parentheses are standard errors of the means
[2]Man Equivalent Units (MEU) were calculated following Runge-Metzger (1988) as: < 9years = 0; 9 to 15 and over 49 years = 0.7; 16 to 49 = 1.
[3]Off farm activities included remittances, sale of charcoal and petty trading.

3.3 Estimating the causal impact of improved fallows using matching approaches

The results of the propensity score used in estimating the matching algorithms are shown in appendix I. The explanatory variables used in estimating the propensity score are shown and described in Table 4 that only include variables showing significant differences between adopters and non adopters. The other variables that did not show any significant differences between the adopters and non adopters included age of household age, whether married, single, widowed or not, whether households experienced soil fertiliser challenges or not, and the camp area dummies (Nyagwena, Katoba and Chainda).

Table 4: Descriptive statistics of significant variables used in estimating the propensity score and outcome models

Variable	Definition	Adopters (N = 111)	Non-adopters (N = 213)	Over all (N = 324)
Education	Years of formal education of household head	3.25 (0.103)***	2.75 (0.075)	2.95 (0.062)
Marital status	1 if divorced, 0 otherwise	0.01 (0.009)*	0.04 (0.013)	0.03 (0.009)
Totfertuse	Total Fertiliser Use (tons)	0.44 (0.039)*	0.31 (0.034)	0.35 (0.026)
SandySoil	1 if farm has sandy soils, 0 otherwise	0.32 (0.045)***	0.15 (0.025)	0.32 (0.045)
Farmsi	Size of farm in hectares	5.16 (0.279)***	3.25 (0.133)	3.90 (0.139)
AreaFa	Size of fallowed land in hectares	1.78 (0.199)***	1.02 (0.094)	1.28 (0.094)
HsizeE[2]	Number of MEU in a household	4.55 (0.181)***	3.81 (0.124)	4.06 (0.104)
Group	1 if household belongs to agricultural group, 0 otherwise	0.96 (0.018)***	0.66(0.033)	0.77 (0.024)
Windex[3]	Household wealth index	0.605***	-0.257	0.0386

*, **, *** significant difference between adopters and non-adopters means at 90%, 95% and 99% confidence levels,[1] see Table 1 for the definition of categories.
[2] Man Equivalent Units (MEU) calculated following Runge-Metzger (1988) as: < 9years = 0; 9 to 15 and over 49 years = 0.7; 16 to 49 = 1 were used to MEU in households.
[3] computed for household assets using principal component analysis following Langyintuo (2008)

Matching results are reported in Table 5 for the nearest neighbour method and Table 6 for the kernel matching approach. The nearest neighbour strategy used 43 households among the control units to match against 110 adopting households. Using the nearest neighbor matching strategy, the improved fallow technology showed positive impact in some but not all of the welfare indicators considered. For the 2010/2011 season, the technology had a significant impact on per capita maize income, total maize yields, per capita maize yields, maize yields per hectare and the number of months in a year the household had enough own grown food for consumption. The technology did not have a significant impact on per capita crop income (Table 5).

Table 5: ATT estimation of various outcome variables using Nearest Neighbour Method

	Average Treatment on Treated(ATT)	Standard Error	t value
Crop Income per MEU (ZK, 000)	180	219	0.825
Maize Income per MEU (ZK, 000)	509	130	3.914
Total Maize yield (tons)	1.99	0.533	3.737
Maize yield per MEU (tons)	0.532	0.160	3.323
Maize yield (ton/ha)	0.568	0.242	2.345
Months per year with enough grown food	1.264	0.465	2.720

Number of treated units used =110 and number of control units used = 43
[1]Man Equivalent Units (MEU) were calculated following Runge-Metzger (1988) as: < 9years = 0; 9 to 15 and over 49 years = 0.7; 16 to 49 = 1.

The kernel matching strategy used more control units (192) to match against the 110 adopting households. Unlike the nearest neighbour approach, the kernel matching strategy results showed that the technology had positive and significant impacts on all the welfare variables considered. It had a positive impact on per capita maize income, total maize yield, per capita maize yield, maize productivity and months per year a household has enough food. In addition the technology had positive and significant effect on per capita crop income (Table 6).

Table 6: ATT estimation of various outcome variables using Kernel Matching

	Average Treatment on Treated (ATT)	Standard Error	t value
Crop Income per MEU (ZK, 000)	331	165	1.999
Maize Income per MEU (ZK, 000)	487	127	3.824
Total Maize yield (tons)	1.776	0.371	4.793
Maize yield per MEU (tons)	0.483	0.119	4.070
Maize yield (ton/ha)	0.718	0.182	3.941
Months per year with enough grown food	1.069	0.323	3.311

Number of treated units used = 110 and number control units used = 195
[1]Man Equivalent Units (MEU) were calculated following Runge-Metzger (1988) as: < 9years = 0; 9 to 15 and over 49 years = 0.7; 16 to 49 = 1.

3.4 Estimating the causal impact of improved fallows using endogenous switching regression models

The full information maximum likelihood estimates of the endogenous switching regression model are shown in Tables IIa to IIe in the appendix. The first and second columns in these tables present the welfare functions for households that did and did not adopt the improved fallow technology while the last column represent the selection equation on adopting improved fallows or not. The correlation coefficient (rho) between the adopter's regime and the selection equation in the total maize yields model is negative and significantly different from zero. This suggests that farmers who adopted improved fallows get higher maize yields than a random farmer from the sample would have obtained. There exist both observed and unobserved factors influencing the decision to adopt improved fallows and this welfare outcome given the adoption decision.

The switching regression model's results on the expected welfare outcomes under actual and counter factual conditions are shown in Table 7. The results still indicates that the technology has a positive impact on maize income per capita, total maize yields, maize yield per capita and maize yield per hectare. The mean values of these outcome variables were significantly higher for adopters than had they not adopted. The gap in the mean crop income value was however not significant (Table 7). The switching regression model also predicted a positive and significant effect of the technology on all the welfare variables on the non-adopters had they adopted. In fact the effect of the technology on the non-adopters could have been much higher than on the adopters in all outcome variables except maize yield per hectare.

The treatment effects on the adopters from switching regression were generally lower than those from the matching strategies. For instance while the per capita maize income ATT was estimated at ZK509, 000 and ZK 487, 000 using the nearest neighbour and kernel matching strategies, the switching regression model gave an estimate of about ZK300, 000.

Table 7: Endogenous switching regression model results

	Decision stage		Treatment effect
	Adopted	Not to adopt	Difference (TT or TU)
a) Crop income per meu (ZK)			
Adopters	1,160,054 (57580)	1,087,408 (56176)	72,645 (64445)
Non-adopters	1,484,130 (57211)	648,600 (34577)	835,530(63611)***
Heterogeneity effects	BH_1 = -324,076	BH_2 = 438,808	TH = -762,885
b) Maize income per meu (ZK)			
Adopters	812,108 (48408)	511,903 (35473)	300,205 (41500)***
Non-adopters	902,821 (40306)	304,951 (20519)	597,871 (32714)***
Heterogeneity effects	BH_1 = -90,713	BH_2 = 206,952	TH = -297,665
c) Maize yield (ton)			
Adopters	5.94 (0.281)	4.62 (0.230)	1.32 (0.170)***
Non-adopters	6.59 (0.146)	2.12 (0.104)	4.46 (0.121)***
Heterogeneity effects	BH_1 =-0.65	BH_2 = 2.5	TH = -3.15
d) Maize yield per meu (ton)			
Adopters	1.24 (0.065)	1.16 (0.054)	0.0794 (0.051)*
Non-adopters	1.72 (0.045)	0.63 (0.031)	1.093 (0.038)***
Heterogeneity effects	BH_1 = -0.48	BH_2 = 0.53	TH = -1.01
e) Maize yield per hectare (ton)			
Adopters	2.214 (0.049)	1.40 (0.033)	0.81 (0.053)***
Non-adopters	2.209 (0.043)	1.46 (0.023)	0.747 (0.050)***
Heterogeneity effects	BH_1 = 0.005	BH_2 = -0.06	TH = 0.065

TT = treatment effect on the treated (adopting – had not adopted), TU = treatment effect on the untreated (had they adopted – not adopted), BH = Base heterogeneity (adopted – had they adopted), TH = Transitory heterogeneity (TT – TU)

4. DISCUSSION

The evaluation of impact of adoption of a technology requires meaningful estimation so that over or under estimation is avoided. This study was concerned with the estimation of the impact of improved fallows on farmer welfare. The study used data from 324 households surveyed in Chongwe district of Zambia to demonstrate the causal effect of the improved fallow technology by using well established identification strategies. Our findings showed that without randomization there is a tendency to over estimate the impact of improved fallows on farmer welfare variables. By simply using 'the conventional t test approaches' in analyzing the differences in various outcome variables, adopters were found to be well off than the non-adopters. The adopters had significantly higher levels of per capita incomes, crop incomes and incomes from maize. In addition, the maize yields and maize productivity were higher than those of non-adopters. The adopters also had more months in which they were sufficient in home grown food and were wealthier in terms of assets than the non-adopters. On the other hand the non-adopters had more off farm incomes than the adopters.

Without rigorous analyses, the mean differences in the outcome variables considered were so significantly high that an attempt to infer to improved fallows as the cause of these differences cannot be ruled out. Evaluating impact of improved fallows using more rigorous econometric analytical tools confirmed the positive impact of improved fallows on per capita income, maize income, maize yield, maize yield per hectare and number of months per year the household has enough home grown food. Estimations from both the matching strategies (nearest neighbour and kernel) and endogenous switching regression model indicated that the technology has a positive and significant impact on the welfare variables noted above. Notably, the technology's positive impacts appear to be more pronounced with outcome variables that are closely related with the maize crop. This is not surprising since the most common crop grown after the improved fallows is maize (Sileshi et al. 2008). Maize being the staple food in Zambia and most parts of sub Saharan Africa, the contribution of the improved fallows in ensuring food security and hence alleviating food poverty cannot be over emphasized.

There however was a contrast in the findings from kernel and nearest neighbour matching strategies on the impact of the technology on crop income per capita. The former method showed a positive and significant impact of the technology on crop income while the latter method showed that the effect was insignificant. The insignificance of the technology to influence crop incomes was also confirmed by the more robust endogenous switching regression which accounted for the unobserved bias. There are two explanations that this finding seems to suggest. First, it might be that other soil improvement options are the ones driving the increases in crop income. A closer scrutiny of our data showed that 89.2% of the adopters of improved fallows were also using inorganic fertilisers. The impact of fertiliser on crop income and other welfare indicators may need to be investigated further. Second, this finding could reflect the fact that the improved fallow technology is not necessarily being used on high value crops such as cotton and some horticultural products that are common in the study area. Most farmers in the study area are aware that the technology improves soil fertility. However there is little evidence to suggest that farmers are aware that any crop can fairly do well on the soils improved by the technology other than maize. Maize was the only crop planted after improved fallows by all the adopters. There might be need to sensitize farmers on the need to grow high value crops on improved fallow plots as well.

Results from switching regression also showed that they would have been a significant positive treatment effect if the non-adopters had adopted the technology. Although a detailed adoption study would provide insights into the factors constraining adoption of the technology, more than 80% of the non adopters cited the long waiting period (for accrual of benefits) as the main reason for not taking up the technology. Research at KATC is actively pursuing the issue of short duration improved fallows. Key informant interviews revealed that it is the more reason why pigeon pea is the most common improved fallow specie in the study area. Compared to others such as *Sesbania*, *Tephrosia* and *Gliricidia* improved fallows that require at least 2 years to reach fallow maturity, some pigeon peas species have been known to reach maturity after only 1 year. There is need therefore to promote such species among the small scale farmers in a much more vigorous way.

The matching techniques and the switching regression model accounted for observables and unobservable factors such as differences in management skills between the adopters and non-adopters. In essence we created a quasi experimental design in estimating the impact of the improved fallow technology. We therefore expected the causal effect of the technology to approximate the productivity yields from randomised experimental trials. The causal effect of the improved fallows on maize productivity was estimated at about 800kg per hectare. Mafongoya et al (2006) showed that improved fallows on randomised experimental plots in eastern part of Zambia can give up to 3,000 – 4,000 kg of maize per hectare in the first year of fallow termination. In subsequent years, the yields decline up to around 1,500 kg after 3 years or so. The 800kg of maize per hectare estimated is far from these figures. This gives some evidence that the farmers' skills in the management of the improved fallows and probably the maize crop as well, may not be very good. For the farmers to get optimum yields there is need to continuously train them in management of new improved agricultural technologies such as improved fallows.

By analyzing crop income estimates from the robust econometric methods, one could easily dismiss the positive impact of improved fallows. Conversely, assessing the outcome variables that are closely associated with improved fallows such as maize yield, one could quickly conclude that improved fallows have a positive effect on household welfare. This suggests that the measurement of welfare needs to be contextualized. Household welfare may have different meaning to different stakeholders. This study deliberately used a broad list of these welfare variables so that an assessment of the stage at which improved fallows cease to have impact on the household well being may be established. This is important so that policy makers know exactly were to target in the promotion of technologies. For instance, general agricultural developmental support might not necessarily boost the uptake of improved fallows. This is because some technologies that are used on high value crops such as inorganic fertilizer might have a significant influence on broader variables such as crop income. In this case price support policies that directly impact on maize production and exchange could be more meaningful in having a 'pull effect' on the adoption of improved fallows.

5. CONCLUSION

We estimated the causal effect of improved fallows on several outcome variables among resource poor small scale farmers in Chongwe district of Zambia. We used propensity score matching techniques complemented with endogenous switching regression models to ensure results robustness. The estimates from these methodologies show that there is a causal effect of the technology on maize production, productivity, per capita maize yield and maize income. Maize productivity from these quasi-experimental designs was lower than that from randomized experimental trials suggesting the need for continuous training of famers in management of improved fallows. The maize income from the technology was also not observed to have had a significant influence on overall crop income. This highlights the importance of diversifying the use of the technology on other high valued crops. Estimates from the econometric methods were generally lower than those from the conventional evaluation without randomization suggesting the need for researchers to adopt more robust evaluation methodologies in impact assessment of technologies.

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Appendix

Table I: Estimated propensity score results

Variables	Coefficient	Standard error	Z
HHage	0.125**	0.0541	2.30
HHedu	0.258	0.423	0.61
MaleHH	-0.106	0.360	-0.30
HsizeE	0.0248	0.0526	0.47
Marr	0.845	0.768	1.10
Sing	1.825**	0.827	2.21
Wid	1.143	0.784	1.46
HHage2	-0.00138***	0.000535	-2.58
HHedu2	-0.0267	0.0658	-0.41
SoilfertCH	0.169	0.178	0.95
SandySoil	0.349	0.213	1.64
Farmsi	0.238***	0.0760	3.13
AreaFa	-0.00439	0.0923	-0.05
Group	1.280***	0.313	4.09
Totfertuse	-0.388*	0.212	-1.83
Windex	0.285**	0.118	2.42
Chainda	0.391*	0.228	1.71
Nyangwena	-0.798***	0.268	-2.98
Constant	-6.474***	1.642	-3.94
Observations	321		
LR Chi2 (18)	136.91		
Prob > chi2	0.0000		
Pseudo R2	0.33		

Table IIa: Full information maximum likelihood estimates of the switching regression model

Dependent variable: Crop income (ZK) per man equivalent during 2010/2011season for Chongwe District

Variables	CropIncper_1	CropIncper_0	IF2006
HHage	-100,429	66,265*	0.191***
	(92,703)	(36,859)	(0.0521)
HHedu	-792,704	444,527	0.170
	(514,335)	(318,674)	(0.416)
MaleHH	676,304	107,200	0.0284
	(475,763)	(234,029)	(0.321)
HsizeE	-206,852***	-175,521***	0.0212
	(62,469)	(41,001)	(0.0489)
Marr	-2.471e+06**	467,810	0.745
	(1.190e+06)	(412,783)	(0.693)
Sing	-2.424e+06*	436,668	1.534**
	(1.237e+06)	(531,256)	(0.755)
Wid	-2.205e+06*	146,897	0.863
	(1.155e+06)	(444,508)	(0.718)
HHage2	894.3	-516.4	-0.00195***
	(903.7)	(367.4)	(0.000521)
HHedu2	117,004	-60,382	-0.0114
	(76,970)	(50,904)	(0.0643)
SoilfertCH	380,288*	95,557	0.0993
	(209,649)	(137,800)	(0.169)
SandySoil	-586,476**	441,729**	0.371*
	(256,032)	(196,051)	(0.204)
Farmsi	204,986***	204,368***	0.298***
	(76,754)	(68,108)	(0.0657)
AreaFa	-273,847***	-202,879***	-0.0558
	(94,490)	(73,330)	(0.0857)
Chainda	148,341	-304,492*	-0.0338
	(269,528)	(172,545)	(0.202)
Nyangwena	487,729	-403,888*	-0.883***
	(392,562)	(227,752)	(0.258)
Constant	7.240e+06**	-2.107e+06*	-7.125***
	(3.193e+06)	(1.083e+06)	(1.554)
Rho	-0.0115	-0.135	
	(0.286)	(0.362)	

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table IIb: Full information maximum likelihood estimates of the switching regression model

Dependent variable: Maize income per man equivalent unit during 2010/2011 season for Chongwe District

Variables	HhldPerMzIn_1	HhldPerMzIn_0	IF2006
HHedu	-684,416	223,473	0.322
	(443,003)	(208,401)	(0.390)
MaleHH	76,024	48,507	-0.0459
	(398,474)	(155,805)	(0.314)
HsizeE	-155,468***	-87,273***	0.0463
	(51,048)	(26,417)	(0.0450)
Marr	-508,089	196,947	0.693
	(1.009e+06)	(273,885)	(0.695)
Sing	-1.066e+06	-4,070	1.418*
	(1.053e+06)	(356,897)	(0.749)
Wid	-698,277	184,381	0.822
	(983,742)	(296,736)	(0.713)
HHedu2	115,339*	-26,179	-0.0337
	(65,674)	(33,516)	(0.0607)
SoilfertCH	213,111	-8,304	0.0833
	(177,587)	(91,319)	(0.165)
SandySoil	-524,066**	17,771	0.390**
	(218,700)	(131,878)	(0.197)
Farmsi	175,694**	178,391***	0.298***
	(72,281)	(47,626)	(0.0618)
AreaFa	-227,988***	-165,606***	-0.0641
	(78,979)	(48,878)	(0.0821)
Chainda	-178,659	-28,429	0.0415
	(221,296)	(110,038)	(0.191)
Nyangwena	447,449	-82,714	-0.794***
	(340,163)	(147,392)	(0.249)
Constant	2.457e+06	-352,301	-2.926***
	(1.515e+06)	(438,467)	(0.912)
Rho	-0.594	0.0848	
	(0.452)	(0.250)	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table IIc: Full information maximum likelihood estimates of the switching regression model

Dependent variable: Household maize production during 2010/2011 season for Chongwe District

Variables	Totmzyield_1	Totmzyield_0	IF2006
HHage	-0.440**	0.0284	0.163***
	(0.207)	(0.0637)	(0.0539)
HHedu	-2.636**	0.462	0.345
	(1.207)	(0.595)	(0.404)
MaleHH	-1.159	0.0866	0.00228
	(1.105)	(0.438)	(0.316)
HsizeE	-0.0789	-0.0469	0.0138
	(0.148)	(0.0772)	(0.0488)
Marr	-1.782	0.909	0.648
	(2.602)	(0.766)	(0.713)
Sing	-4.563*	0.170	1.432*
	(2.758)	(0.964)	(0.773)
Wid	-2.845	0.494	0.909
	(2.528)	(0.825)	(0.730)
HHage2	0.00396*	-1.27e-05	-0.00174***
	(0.00203)	(0.000633)	(0.000539)
HHedu2	0.402**	-0.0295	-0.0453
	(0.184)	(0.0951)	(0.0627)
SoilfertCH	-0.0874	0.0426	0.0415
	(0.502)	(0.256)	(0.169)
SandySoil	-0.655	0.0304	0.345*
	(0.657)	(0.359)	(0.204)
Farmsi	0.370**	0.608***	0.205***
	(0.175)	(0.127)	(0.0693)
AreaFa	-0.897***	-0.756***	0.0307
	(0.240)	(0.145)	(0.0842)
Windex	1.297***	0.712***	0.345***
	(0.315)	(0.193)	(0.109)
Chainda	-0.0713	-0.0814	0.188
	(0.634)	(0.329)	(0.212)
Nyangwena	1.860*	-0.108	-0.671***
	(0.950)	(0.402)	(0.256)
Constant	24.16***	-1.889	-6.224***
	(6.616)	(1.921)	(1.601)
Rho	-1.312**	0.0782	
	(0.542)	(0.220)	

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table IId: Full information maximum likelihood estimates of the switching regression model

Dependent variable: Maize production per hectare during 2010/2011season for Chongwe District

Variables	Mzydperha_1	Mzydperha_0	IF2006
HHage	-0.133	0.0573*	0.187***
	(0.105)	(0.0345)	(0.0505)
HHedu	0.119	0.279	0.239
	(0.566)	(0.309)	(0.408)
MaleHH	1.135**	0.0117	0.0674
	(0.517)	(0.234)	(0.312)
HsizeE	-0.0616	-0.0405	0.0138
	(0.0683)	(0.0412)	(0.0474)
Marr	-0.956*	0.440*	-0.245
	(0.501)	(0.245)	(0.311)
HHage2	0.00114	-0.000494	-0.00194***
	(0.00103)	(0.000343)	(0.000506)
HHedu2	-0.0297	-0.0321	-0.0217
	(0.0843)	(0.0500)	(0.0635)
SoilfertCH	-0.179	0.0392	0.146
	(0.235)	(0.138)	(0.167)
SandySoil	0.00363	-0.226	0.372*
	(0.283)	(0.207)	(0.203)
Farmsi	0.0509	0.0856	0.307***
	(0.0881)	(0.0714)	(0.0649)
AreaFa	-0.0563	-0.0827	-0.0521
	(0.105)	(0.0762)	(0.0851)
Chainda	-0.230	-0.355**	-0.0615
	(0.299)	(0.176)	(0.199)
Nyangwena	-0.527	-0.624***	-0.911***
	(0.443)	(0.224)	(0.253)
Constant	5.856*	-0.585	-6.126***
	(3.276)	(0.857)	(1.346)
rho	-0.865	0.0781	
	(0.137)	(0.219)	

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table IIe: Full information maximum likelihood estimates of the switching regression model

Dependent variable: Maize yield per man equivalent unit during 2010/2011 season for Chongwe District

Variables	MzyldperMeu_1	MzyldperMeu_0	IF2006
HHage	-0.0470	0.0262	0.194***
	(0.0637)	(0.0221)	(0.0524)
HHedu	-0.985***	0.140	0.195
	(0.341)	(0.197)	(0.414)
MaleHH	0.327	0.0538	0.0850
	(0.315)	(0.145)	(0.326)
HsizeE	-0.230***	-0.174***	0.0215
	(0.0422)	(0.0253)	(0.0477)
Marr	-1.041	0.266	0.688
	(0.807)	(0.254)	(0.692)
Sing	-1.158	-0.131	1.528**
	(0.854)	(0.325)	(0.752)
Wid	-0.782	0.0566	0.903
	(0.765)	(0.274)	(0.712)
HHage2	0.000477	-0.000125	-0.00198***
	(0.000627)	(0.000220)	(0.000526)
HHedu2	0.142***	-0.00868	-0.0175
	(0.0513)	(0.0315)	(0.0640)
SoilfertCH	0.0264	0.0810	0.0961
	(0.139)	(0.0852)	(0.169)
SandySoil	-0.212	0.110	0.341
	(0.180)	(0.120)	(0.210)
Farmsi	0.168***	0.232***	0.309***
	(0.0494)	(0.0410)	(0.0662)
AreaFa	-0.277***	-0.240***	-0.0607
	(0.0638)	(0.0454)	(0.0851)
Chainda	0.00675	-0.184*	-0.0323
	(0.178)	(0.107)	(0.202)
Nyangwena	0.387	-0.154	-0.888***
	(0.277)	(0.138)	(0.256)
Constant	5.498**	-0.635	-7.200***
	(2.261)	(0.653)	(1.556)
Rho	-0.594	0.0848	
	(0.452)	(0.250)	

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$