ROBUST STRATEGIES TO ISOLATE THE CAUSAL EFFECT OF IMPROVED FALLOWS ON FARMER WELFARE AND ONFARM ENVIRONMENTAL QUALITY IN ZAMBIA

By

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DEDICATION

This work is dedicated to my four ladies; my mother Janet, daughters Jane and Tracy Tapiwa, and my wife Unity. Thanks for all the support.

DECLARATION

I hereby declare that the dissertation I submit for the degree of PhD Environmental Economics at the University of Pretoria is entirely my work and has not been submitted anywhere else for the award of a degree or otherwise.

Part of the thesis have been published and submitted for publication to journals

Signed: ....

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Date: July 2014

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ABSTRACT

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This study attempts to explain the inability of resource constrained farmers in Zambia to invest in soil fertility enhancing improved fallows, a sustainable land use practice developed by the World Agroforestry Centre (ICRAF) in the 1980s. Although several studies in the laboratory and field have shown that improved fallows positively impact on farmers' welfare, the reliability of such conclusions comes into question given their use of improper identification strategies. Secondly, although there is general consensus that improved fallows additionally co-produce environmental services, the literature acknowledges that such services are not only imprecisely defined but also rarely quantified. Most estimates for environmental services have been confined to controlled field trials and laboratory experiments. Consequently, this research was designed to answer the following questions: 1) Would the use of randomisation procedures to estimate impact provide additional support to the foregone conclusions by most literature regarding the positive impact of improved fallows on farmer welfare? 2) Studies from on-station experiments

show that improved fallows provide environmental services; do such conclusions hold for improved fallows planted on-farm where the near ideal experimental conditions are not guaranteed?

A structured questionnaire was used to interview 324 randomly selected small scale farmers in Chongwe district of Zambia between November and December 2011. The data was analysed using well-grounded and robust matching and switching regression counter factual analysis tools.

The rigorous econometric methods confirmed the positive impact of improved fallows on household maize yields, maize productivity, per capita maize yield and maize income. Insignificant impact results were however obtained when broader welfare indicators – overall per capita, crop income and value of crop production were considered. The study attributes these later results to two possible areas; first, most of the maize sold that contributes to crop income may be coming from other input sources such as the inorganic fertiliser that is common in the study area. Second, the non-use of the technology on cash crops (for example cotton) in subsequent periods after a year or two of maize cropping reduces the technology's contribution to the households' cash crop income portfolio. Had the study only used maize income or value of maize income to measure overall crop income (or value of crop production), or had it just made a simple comparison between adopters and non adopters, the likelihood of not finding any insignificant results on the efficacy of improved fallows would have been high. The study thus concludes that the use of improved fallows should be diversified to cover the entire cash crop portfolio especially a year or so after maize cropping when most of the nitrogen supplied by technology has been used up. More importantly, the study recommends use of better and more robust methodologies in evaluating impact of interventions.

The positive effects of improved fallows on on-farm environmental quality, controlling for farmers' biophysical and socio-economic characteristics were confirmed. Estimates from OLS regression, matching and the more robust endogenous switching regression showed that the technology had a significant causal effect on households' consumption of fuel wood obtained from natural forests. The technology can provide up to 1,086 kg or about 51% of annual household fuel wood requirements in the year the fallows are terminated. This amount is substantial enough to make a positive contribution towards reducing encroachment on public

forests and thus control the rate of deforestation. In addition to promoting the technology for soil fertility improvement (the role which is widely accepted by the farmers), explicit extension messages conveying the technology's capacity to provide various products that contribute to farmer welfare as well as provide on farm environmental quality should be made available.

Key words: Cause-effects estimates, environmental services, natural forest protection, fuel wood, matching strategies, identification strategies, improved fallows

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LIST OF ACRONYMS

ATT	Average Treatment Effect on the Treated
CIA	Conditional Independence Assumption
FRA	Food Reserve Agency
KATC	Kasisi Agricultural Training Centre
KM	Kernel Matching
NN	Nearest Neighbour
ICRAF	International Centre for Research in Agroforestry
IV	Instrumental Variable
NRM	Natural Resources Management
OLS	Ordinary Least Squares (OLS)
GRZ	Government of the Republic of Zambia
UP	University of Pretoria
UNZA	University of Zambia

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

During the green revolution era of the late 1960s and 1970s, intensification of agricultural production and productivity through the use of inorganic fertilizers increased in importance. Huge success of the green revolution in most parts of the world helped in increasing crop production as well as productivity and ensuring food security of several countries. Over time such agricultural growth which was achieved through intensive and increased use of inorganic fertiliser started posing serious challenges to environmental sustainability. Generally agricultural intensification is associated with the diminishing capacity of natural systems to continue supplying ecosystem services. For instance it has been noted that intensification of production methods to increase agriculture production in the 1970s has caused increased environmental pollution (van der Werf & Petit, 2002). Experience shows that a policy that advocates for increased inorganic external inputs increases short-run productivity at the expense of long-run environmental performance. There are trade-offs involved between intensifying agricultural production and the ability of ecosystems to produce environmental services. The general approach is to motivate research that minimises trade-offs and promotes synergies. There are some land management practices that minimises trade-offs while others promote synergies. However few land management practices exist that simultaneously minimises these trade-offs while at the same time promote the synergies.

In an effort to simultaneously contribute towards increased crop production and productivity while at the same time provide an environmentally sustainable land management practise; the improved fallow was developed by the World Agroforestry Centre for use in Zambia and elsewhere in the sub-Saharan African region. An improved fallow builds on the traditional shifting cultivation farming methods that leave land for an extended period of time to ensure the regeneration process to take place. The difference however is that, with improved fallows, the fallow period is drastically reduced. Improved fallows are fast growing trees that are grown for 2 – 3 years and that rapidly fix atmospheric nitrogen (N) in the soil and this nitrogen is made available to the subsequent or intercropped crop thereby increasing yields for those crops mostly dependent on nitrogen. The main species used as improved fallows in Zambia and many parts of Sub-Saharan Africa include; *Gliricidia sepium* (Mexican lilac), *Cajanus cajan* (Pigeon pea), *Sesbania sesban* (River bean), *Tephrosia vogelii* (Fish bean) and *Faidherbia albida* (Winter thorn). In addition to soil fertility improvement that subsequently increase crop yields and hence farmer welfare (Akinnifesi, *et al*. 2006; Ajayi, *et al*. 2007; Franzel, 2004; Place, *et al*. 2002; Quinion, *et al*. 2010), literature claims that improved fallows also provide environmental public goods such as carbon sequestration, reduced nitrogen leaching, improved biodiversity, provision of fuel wood and improved soil structure among other services (Sileshi, *et al*. 2007).

Despite the potential benefits from the technology, diffusion of improved fallows among resource constrained smallholder farmers have lagged behind scientific and technological advances (Akinnifesi, *et al*. 2006; Ajayi, *et al*. 2007). This study acknowledges that farmers like any other economically rational individuals are profit maximisers, therefore if they observe that improved fallows are profitable, profit maximisation theory suggests that they should voluntarily take up the technology (behavioural response) since this will increase their welfare. This is especially true for resource constrained farmers with limited alternatives to improving their on farm soil fertility. Since this is not observed, some studies (Keil, *et al*. 2005; Ajayi, *et al*. 2003) have analysed factors affecting the adoption of the technology and thus given recommendations to better the environment for adoption. However, no significant increases in adoption rates have been noticed even where conditions for adoption are favourable. The question begging answers is whether the technology significantly increases farmer welfare. Second, studies (Chirwa, *et al*. 2007; Makumba, *et al.* 2007; Sileshi, *et al*. 2007) have used estimates from experimental data to claim that the technology can provide on-farm environmental quality. Some studies (Kohlin & Parks, 2001; Patel, *et al*. 1995; Pattanayak & Depro, 2004) that have incorporated socioeconomic characteristics of the farmers to estimate the technology's ability to prevent deforestation through the provision of on farm fuel wood have also failed to give precise estimates of the actual quantities of wood replaced.

A critical review of studies citing the positive benefits of the technology towards farmer welfare and on-farm environmental quality show that the evaluation approaches have not been rigorous. The general argument in this study is that the results of an impact assessment study might depend on the measurement approach. Less rigorous approaches could produce misleading estimates of the impact of the technology. Impact assessment involves analysing whether the changes in outcome variables are indeed due to technology adoption and not to other factors. The central issue that forms the cornerstone of this study is whether the changes in farmer welfare variables or on-farm environmental quality had solely been attributed to improved fallow adoption.

Studies cited above have mostly used profitability ratios and simple adopter and non-adopter comparisons to come to conclusions that the improved fallows improve farmer welfare. The problem with simple comparisons is that the adopters and non-adopters may not be the same prior to the intervention, so the expected difference in outcome variables between the groups may not solely be due to adoption of the improved fallows. The difference in farmer welfare between the two groups in the absence of technology adoption can be attributed to selection effect (SE). Therefore the observed difference in welfare due to uptake of improved fallows includes the difference attributed to the selection effect or bias. Since the counterfactual of adopters is not known, it is difficult to estimate the magnitude of selection bias. By extension therefore, it is difficult to know the extent to which selection bias makes up the observed difference in outcomes between the adopters and non-adopters. Robust impact assessment approaches attempts to account for this selection bias. This is done through the creation of the counterfactual or a situation the adopting farmer would have experienced had he not adopted. A summarised version of different ways to create this counterfactual in the case of data from a one cross section survey like in this study's case are discussed below.

First, randomisation in treatment assignment can help towards tackling the problem of selection bias or effect discussed above. According to Taylor *et al.* (2012), the selection effect disappears if treatment assignment is completely random. This is because it eliminates the economic decisions that drive the treatment choice. In the context of this study, if improved fallows adoption is completely random, then there is no problem with regards to selection effect. In general randomisation's goal is to make sure that the farms adopting the improved fallows and those not, have an equal probability of adopting the technology. In practice, it is difficult to randomly select farmers who would want to benefit from a poverty reducing technology such as improved fallows. Moreover this study is an ex post evaluation analysis thus there was no control in the selection of adopters of the technology.

With a randomised sample, the simplest evaluation technique to examine the causal effect of adoption of improved fallows on either welfare or on-farm environmental outcome would be to include in the regression equation a dummy variable equal to one if the farm adopted improved fallows and zero otherwise. However, according to Asfaw (2010), this might still yield biased estimates since adoption is potentially endogenous and not entirely exogenously determined. Systematic different characteristics among farmers who adopted from the farmers that did not adopt may still exist. Unobservable characteristics of the farmer and the farm environment may affect both the adoption decision and the outcomes, resulting in inconsistent estimates of the causal effects of adoption of improved fallows. Although Hausman (1978) suggests the explicit accounting for such endogeneity using simultaneous equation models, it may still be inappropriate to use a pooled sample of adopters and non-adopters (with a binary indicator for adoption or not) since this would assume that technology adoption has an average impact over the entire sample of farmers, by way of an intercept shift, or that it raises the productivity of factors of production, by way of slope shifts in the outcome functions (Alene & Manyong, 2007).

Secondly, it is also possible to randomise the farmers using matching approaches. Matching is a form of randomisation that assumes away the selection effect by assuming that selection is based on observables (Caliendo & Kopeinig, 2005). If all observable characteristics can be used to match adopters and non-adopters, then the causal effect of improved fallows on farmer welfare or on-farm environmental indicators can be compared using like or similar groups of farmers. Although matching methods are intuitively easier, the assumption that selection bias is based only on observed characteristics is its main weakness. Matching can not account for unobserved factors influencing adoption of technologies.

Thirdly, since we are concerned with correlation of the treatment variable (improved fallow adoption) with the errors, a randomly assigned variable (instrument) that would not affect the outcome variable except through its effect on the treatment can be used. This is called instrumental variable (IV) approach. The instrument should be correlated with adoption of improved fallows but uncorrelated with either farmer welfare or on-farm environmental quality so that by extension it should not be correlated with the error term. The main weakness with this approach is that it is very difficult to find such an instrument.

Fourthly, the Heckman Selection Estimator can be used. According to Brundell & Dias (2000) this evaluation method is more robust than the IV estimator although it also demands more assumptions about the structure of the model. The rationale of this estimator is to control directly for the part of the error term in the outcome equation that is correlated with the treatment or adoption dummy variable (Brunbell & Dias, 2000). The Heckman procedure follows two steps. First, the part of the error term that is correlated with treatment is estimated. The estimated part is then included in the outcome equation and the effect of treatment is estimated in a second step. By construction, what remains of the error term in the outcome equation is not correlated with the treatment participation decision. This model ably accounts for sample selection bias but the use of the two step procedure requires some adjustments to derive consistent standard errors

(Maddala, 1983) and it also does not perform well in case of high multicollinearity between the covariates of the selection equation and the outcome equation (Nawata, 1994).

Finally, more recently an advanced form of a selection model called endogenous switching regression has been used in evaluation studies (Asfaw, 2010). Using maximum likelihood estimation techniques, this model predicts the potential outcomes the adopter (or non adopter) of a technology would get in the two regimes of either adopting or not. The 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 endogenous switching regression model accounts for both endogeneity and sample selection and allows interactions between adoption and other covariates in the outcome function (Freeman, *et al*. 2001; Alene & Manyong, 2007). This study used this model in addition to matching, which is intuitively easy to implement and makes a lot of practical sense in evaluating the impacts of improved fallows. More details on the use of these models are given in Chapter 2 and Chapter 3.

1.2 THE RESEARCH PROBLEM AND JUSTIFICATION

It was noted earlier that farmer investment decisions in most parts of sub Saharan Africa have not favoured sustainable land use practices such as improved fallows. Compared to the conventional inorganic fertiliser, the uptake of improved fallows has generally been sub-optimal. Studies citing improvement in welfare among farmers adopting improved fallows exist (Akinnifesi, *et al*. 2006; Ajayi, *et al*. 2007; Franzel, 2004; Place, *et al*. 2002; Quinion, *et al*. 2010), they show that improved fallows positively impact on farmers welfare. However, the validity or reliability of such studies comes into question given they do not use proper identification strategies. Evaluation of the impact of these technologies on household welfare outcomes have been very limited by lack of appropriate methods, with most of the studies largely failing to go beyond estimating basic incremental benefits and return to investment in the technology. Most of these studies have ignored heterogeneity in several observed and unobserved characteristics between those households that did and those that did not adopt improved fallows. Thus, the studies have failed to isolate the causal effect of improved fallow technologies on farmer welfare. Thus in Chapter two of this study, proper randomisation procedures through matching and endogenous switching regression models are used in estimating the welfare effects of improved fallows on data collected from three camps of Chongwe district of Zambia.

Secondly, there is a general consensus that improved fallows play a protective role to the environment. Several studies (Sileshi, *et al*. 2007; Makumba, *et al*. 2007; Styger & Fernandes, 2006) have shown that improved fallows improve environmental quality through the generation of several ecosystem services. However, there is also acknowledgement that the benefits associated with environmental services are imprecise and rarely quantified (Dixon, 1997), especially at farm level. Most estimates of environmental services provided by improved fallows have been confined to controlled field trials and laboratory experiments. Literature is noticeably thin with respect to economic modelling of environmental services from improved fallows under farmers' field conditions. In this study it is noted that the provision of environmental services on-farm by the improved fallow technology has largely remained empirically untested. Thus, in Chapter 3, this study addresses one of the key challenges of demonstrating the benefits of improved fallows in the provision of environmental services under farmers' field conditions using well designed identification strategies.

The precise estimation of the causal effect of a technology is very important in ensuring proper evidence based agricultural and environmental policy. Encouraging farmers to adopt a technology based on faulty scientific conclusions could be detrimental to policy making. In fact as earlier stated predicting adoption rates amidst imprecise cause effects estimates becomes problematic.

1.3 HYPOTHESES AND OBJECTIVES

Typically evaluation studies on improved fallows tacitly assume that improved fallows have a positive and significant effect on household welfare and on-farm environmental quality while failing to properly assess the impact of the technology. As stated earlier, studies that specifically assess the impact of improved fallows have not used rigorous identification strategies to isolate the causal effect of the technology on outcome variables. This could have led to over estimation of the welfare as well as on-farm environmental performance of the improved fallows. Literature reviewed and stated earlier seems to suggest that the improved fallow is a high impact technology thus its adoptability by farmers should equally be high. The contrary is however what is obtaining on the ground. Therefore it would be reasonable to assume that probably the failure by the studies to use a counter factual in comparing the causal effects of the technology could have led to wrong conclusions on the capacity of the technology to improve farmer welfare. This in turn could be partly responsible for the low adoption rates observed.

According to Dehejia and Wahba, 2002, an important problem of causal inference is how to estimate treatment effects in observational studies situations (like an experiment) in which a group of units is exposed to a well-defined treatment, but (unlike an experiment) no systematic methods of experimental design are used to maintain a control group. It is well recognised that the estimate of a causal effect obtained by comparing treatment group with a non-experimental comparison group could be biased because of problems such as self-selection or some systematic judgment by the researcher in selecting units to be assigned to the treatment.

In this study we use matching and endogenous switching regression strategies which are a possible solution to selection problems. Matching's basic idea is to find in a group of non-participants those individuals who are similar to the participants in all relevant pre-treatment characteristics. If this is done, differences in outcomes of the selected group (control) and of participants can be attributed to the programme (Caliendo & Kopeinig, 2005). Endogenous switching regression goes a step further by forming counter factual within the participating and non participating groups, and uses these to compare the effects of the technology.

With the use of the above stated more robust strategies and the discussion on the importance of isolating the causal effect of the improved fallows on farmer welfare, this study was set out to test the following first null hypothesis:

The adaptation and use of matching and endogenous switching regression strategies in estimating the causal effects of improved fallows will provide similar welfare impact estimates as those provided by non randomised conventional impact methodologies.

The alternative hypothesis is that:

The adaptation and use of matching and endogenous switching regression strategies in estimating the causal effects of improved fallows will provide lower welfare impact estimates than those provided by non randomised conventional impact methodologies.

Secondly, the identification and demonstration of environmental benefits provided by agroforestry practices such as improved fallows on the farm has posed a major challenge to agroforestry proponents (Pattanayak & Depro, 2004). As previously stated, several studies have used experimental data to argue for positive contribution of improved fallows to environmental quality. However, the on farm socioeconomic environment faced by farmers can lead to the technologies producing sub-optimal levels of environmental services by biophysical experimental standards since income, production and information constraints faced by farmers are rarely incorporated in experiments (Pattanayak & Depro, 2004). Where attempts have been made to link on farm general tree planting to conservation of public forests, results have fallen short of providing the actual quantities of forest products that can be replaced. Since improved fallows provide environmental services such as reduction in soil erosion, provision of fuel wood and construction materials, increased soil structure and so forth, that directly benefit the farmers (Ajayi *et al*., 2007), analysing and quantifying in a precise way the levels of these benefits to the farmers could provide some evidence on the technology's potential to provide on farm environmental services. The second null hypothesis of this study was therefore, as stated below:

Farms embracing improved fallows will just be as likely as those not using the technology to be dependent on the natural forests for by-products that are provided by the technology such as fuel wood.

The alternative hypothesis was that:

Farms embracing improved fallows are less likely to be dependent on the natural forests for by-products that are provided by the technology such as fuel wood.

Therefore, the broad objective of the study was to isolate the causal effect of improved fallows on farmer welfare as well as on on-farm environmental quality using more robust identification strategies. The study attempted to achieve the following specific objectives;

1. To quantify the causal effect of improved fallows on several farmer welfare outcome indicators.
2. To quantify the causal effect of improved fallows on households dependency on fuel wood from the natural forests.
3. To formulate relevant policy recommendations premised on more precise estimates of the impact of the technology.

Related to the above objectives this study was designed to answer the following questions:

1. Would randomisation through matching and endogenous switching regression methodologies support the foregone conclusions by most literature regarding the positive impact of improved fallows on farmer welfare?

2. Studies from on-station experiments show that improved fallows provide environmental services; is this necessarily true for improved fallows planted on-farm, where the near ideal experimental conditions are not guaranteed?

1.4 THESIS OUTLINE

This thesis is structured as follows: following this introductory chapter, Chapter 2 discusses estimates of the causal effect of improved fallows on farmer welfare using matching and endogenous switching regression strategies. Various specific policy recommendations are discussed at the end of this chapter. Chapter 3 discusses the causal effect of improved fallows on on-farm environmental quality using OLS regression, matching and endogenous switching regression strategies. The chapter also has specific recommendations that tackle the on farm environmental performance of the technology. Chapter 4 gives a summary on general discussions, conclusions and recommendations of the study.

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CHAPTER 2

ESTIMATING THE CAUSAL EFFECT OF IMPROVED FALLOWS ON FARMER WELFARE USING ROBUST IDENTIFICATION STRATEGIES IN CHONGWE - ZAMBIA

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. Insignificant impact results were obtained when broader welfare indicators – per capita crop income and value of crop production, were considered. 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 was however not sufficient enough to drive the general crop income or value of crop production 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

2.1 INTRODUCTION

Soil fertility problems are widely spread throughout sub-Saharan Africa. Several studies (Sanchez & Jama, 2002; Vanlauwe & Giller, 2006; Mafongoya, *et al*. 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 & 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: 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 analyzed 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 maximising 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 recognised 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 & 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 & 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 and the value of all crops grown on the farm to assess the technology's impact on these broad variables. The econometric methods' estimates confirmed the positive impact of improved fallows on the chosen welfare parameters. However, insignificant impact results were obtained when the broader variables were considered.

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 analysing adopters and non-adopters that were similar in terms of the distribution of covariates. Stated otherwise, the earlier studies could have analysed 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 chapter is structured as follows: theoretical frameworks on adoption, 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.

2.2 METHODOLOGY

2.2.1 Conceptual framework for adoption of improved fallows

Adoption of improved fallows can be viewed as part of the many deliberate activities that a farmer engages in to maximise over all utility on the farm. The households' production and consumption including marketing decisions in a given period are assumed to be derived from the maximisation of expected utility. The optimization takes place in the presence of constraints on the budget, information, credit access and the availability of both the technology and other inputs. Thus, households are assumed to maximize their utility function subject to these constraints. The adoption of improved fallows will occur only if adoption is expected to be profitable. According to Ali & Abdulai (2010), the adoption decision can be modeled in a random utility model. The difference between the utility from adoption (U_{Ai}) and non-adoption (U_{Ni}) of improved fallows may be denoted as G^*, such that a utility-maximizing farm household, *i*, will choose to adopt improved fallows, if the utility gained from adopting is greater than the utility of not adopting ($G^* = U_{Ai} - U_{Ni} > 0$). Since these utilities are unobservable, they can be expressed as a function of observable elements in the following latent variable model:

$$G_i^* = \beta X_i + \mu_i \text{ with } G_i = \begin{cases} 1 & if \quad G_i^* > 0 \\ 0 & otherwise \end{cases} \tag{1}$$

where G is a binary indicator variable that equals 1 if a farmer adopted improved fallows and zero otherwise; β is a vector of parameters to be estimated; X is a vector of explanatory variables; and μ is the error term. The explanatory variables used in the models reported in this study are discussed below.

Most literature on agriculture technology adoption considers that the decision to adopt technologies including improved fallows is affected by the characteristics of the farm household head and the household at large (Ajayi *et al.* 2003; Keil *et al*. 2005). Household heads are the final decision makers who may decide on adoption of new technologies at a farm. The age of the household head is likely to influence adoption of improved fallows. Younger farmers may be more innovative and have lower risk aversion behavior but they may also have less farming experience hence the relationship between age and adoption of improved fallows may be ambiguous. Other farmer and household characteristics such as gender, marital status and level of education are also expected to affect the decision to adopt improved fallows. Female headed households may respond less favourably to adoption of technologies than male headed households due to wealth differences (Ajayi *et al.* 2003). However, some female heads are enthusiastic enough and more willing to try out technologies such as improved fallows. Thus we expect gender of the household head to have an ambiguous effect on adoption of improved fallows. Divorced household heads might have fewer resources for adopting technologies such as improved fallows. However, the divorced household heads could also avoid bureaucratic tendencies of asking their partners (had they been married) in reaching a decision to adopt such technologies. The same applies to single and widowed household heads. Thus marital status of household heads is expected to have an ambiguous effect on adoption of improved fallows. Some educated households would be conservative to adopt improved fallows while others would be more willing to adopt it. The level of education of the household head is also expected to either enhance or discourage adoption. Since improved fallows are labour intensive, household's labour availability is expected to positively affect the farm household's decision to adopt the technology.

In rural Zambia like most developing countries, the level of poverty affects production activities. Assets such as farm sizes, livestock, bicycles, radios and owning an iron roofed house, are expected to enhance adoption of improved fallows and are used in various models as indicators of wealthy. These variables provide production services and are expected to increase the likelihood of adoption for a given household. Inorganic fertiliser use that directly competes with improved fallows adoption can also indicate wealth levels of a household. This variable would discourage the adoption of improved fallows.

If farmers do not experience soil fertility problems, it is unlikely that they will invest labour and capital in improved fallows. Farms that experience soil fertility challenges were postulated to have had a high likelihood of adopting improved fallows. Closely related to soil fertility issues, was the predominant soil type on the farm. Farmers on farms whose soils were predominantly sandy were more likely to adopt improved fallows. The addition of organic matter by the improved fallows to these farms is an additional impetus for the technology's adoption. Farm households with more secure land tenure are expected to be more likely to adopt improved fallows than those that are not (Place *et al*. 2002). Therefore, land tenure security is expected to have a positive effect on adoption of improved fallows. Other factors such as access to information affect adoption of agricultural technologies. Farm households that have such access are expected to be more likely to adopt improved fallows than their counterparts who do not have access. Furthermore, farm households with at least a member belonging to a farmer group are expected to be more likely to adopt improved fallows as farmer groups are expected to be sources of vital farming information. In addition, the study sample came from three agricultural camps; therefore the influence of geographical location would be also important in the adoption of improved fallows.

All these variables were considered in the estimation of the various propensity scores as well as impact estimation models. However due to the matching balancing property condition and the possibility that some variables (such as total fertiliser inorganic fertiliser use, area of fallowed land and group membership) might have been affected by treatment (or the improved fallow) it self, they were dropped. In addition such important variables like land tenure were not included in the estimation of the propensity score because the sample involved in the study were all using customary land. There was no variability in terms of land tenure between the adopters and adopters of improved fallows.

2.2.2 Conceptual 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:

$$E(Y_1 - Y_0) \mid T = 1) \qquad (2)$$

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:

$$Y_0 \coprod T \mid (X\ ) \qquad (3)$$

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 4).

$$Pr(T = 1 | X) < 1. \quad (4)$$

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:

$$e(x) = \Pr(W_i^a = 1 | X_i = x) = E[W_i^a | X_i = x] \quad (5)$$

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 & 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 & Kopeinig, 2005).

2.2.2 Framework for 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;

$$I_i^* = \beta X_i + \alpha Z_i + \mu_i \qquad \text{with} \quad I_i = \begin{cases} 1 & if\ I_i^* > 1 \\ 0 & otherwise \end{cases} \tag{6}$$

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. β and α are vectors of parameters while X_i are vectors of exogenous variables also included in output equations 7 and 8. The exogenous variables included were those that were hypothesised to affect household welfare. Among them included, socioeconomic variables such as the household head's age, education level, marital status; biophysical variables such as households experiencing soil fertility challenges on their farm, whether most parts of the farm is inherently sandy, and some variables serving as indicators of wealth such as farm size and how much land was left fallow in the 2010/11 farming season. To account for area effects, the camp dummy variables were also included. Z_i are non-stochastic vectors of variables that explain only the selection process and have no direct effect on the outcome. These variables are very important for identification purposes. The household yearly fuel wood consumption variable was significantly correlated with adoption of improved fallows but did not have any direct effect on all the welfare outcome variables. This was therefore found to be a suitable instrument and was used in identifying the effects of the technology on maize yields per hectare and maize income per capita. Unfortunately, the models on total maize yield, maize yield per capita and crop income per capita could not converge in the log likelihood estimation when the instrument was used. For these models only the X_i's were used. Because of this weakness, the results of the endogenous switching model for these later models are interpreted with some caution. 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 $I_i = 1$ (7)

Regime 2: $y_{2i} = \beta X_{2i} + \varepsilon_{2i}$ if $I_i = 0$ (8)

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:

$$\Omega = \begin{pmatrix} \sigma_{\mu}^{2} & . & . \\ \sigma_{21} & \sigma_{1}^{2} & . \\ \sigma_{31} & . & \sigma_{2}^{2} \end{pmatrix} \tag{9}$$

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:

$$E[\varepsilon_{1i} \mid I_i = 1] = \sigma_{\varepsilon 1\mu} \frac{\phi(\alpha Z_i)}{\Phi(\alpha Z_i)} = \sigma_{\varepsilon 1\mu} \lambda_{1i} \quad \textit{and} \quad E[\varepsilon_{2i} \mid I_i = 0] = -\sigma_{\varepsilon 2\mu} \frac{\phi(\alpha Z_i)}{1-\Phi(\alpha Z_i)} = \sigma_{\varepsilon 2\mu} \lambda_{2i} \tag{10}$$

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 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 & 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 6, 7, and 8 can be given as follows:

$$InL = \sum_{i=1} \{I_i w[In(\Phi(\eta_{1i}) + In(\phi(\varepsilon_{1i}/\sigma_1)/\sigma_1) + (1-I_i)w_i[In(1-\Phi(\eta_{2i})) + In(\phi/\varepsilon_{2i}/\sigma_2)/\sigma_2]]\} \quad (11)$$

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

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

$$E(y_{1i} / I_i = 1, x_{1i}) = x_{1i}\beta_1 + \sigma_{\varepsilon 1 \mu}\lambda_{1i} \tag{12}$$

(b), that did not adopt the improved fallows

$$E(y_{2i} / I_i = 0, x_{2i}) = x_{2i}\beta_2 + \sigma_{\varepsilon 2 \mu}\lambda_{2i} \tag{13}$$

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

$$E(y_{2i} / I_i = 1, x_{2i}) = x_{2i}\beta_1 + \sigma_{\varepsilon 2 \mu}\lambda_{1i} \tag{14}$$

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

$$E(y_{1i} / I_i = 0, x_{1i}) = x_{1i}\beta_2 + \sigma_{\varepsilon 1\mu}\lambda_{2i} \quad (15)$$

Cases (12) and (13) represent the actual expectations observed in the sample while cases (14) and (15) 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 (12) and (11) 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 (15) and (13).

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 (12) and that of the non-adopters had they adopted (15). Similarly for the group of farm households that decided not to adopt, this is the difference between (14) that the adopters did not adopt and (13) 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.

2.2.3 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.

2.2.4 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 & 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.

2.2.5 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.

2.2.6 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.

2.2.7 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).

2.8 RESULTS

2.8.1 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 labour 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 labour 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 2.1).

Table 2.1: Households socioeconomic characteristics of sample farmers in Chongwe district, Zambia1

	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.

2.8.2 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 2.2). 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 2.2: 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 2.3). 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 2.3).

Table 2.3: 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]
[2]Value Crop Produce per MEU (ZK, 000)	1160 (113)	609 (68)	551 (124)	4.438
Crop Income per MEU[3] (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[4] 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]Value includes maize used for home consumption
[3]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.
[4]Off farm activities included remittances, sale of charcoal and petty trading.

2.8.3 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 Table A2.1 in Appendix 1. The explanatory variables used in estimating the propensity score are shown and described in Table 2.4 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 head, whether married, single, widowed or not, whether households experienced soil fertiliser challenges or not, and the camp area dummies (Nyagwena, Katoba and Chainda). To ensure quality of the match, only those matches whose distribution of the density of the propensity scores overlapped between the adopters and non-adopters observations were used. The distribution of the density of the propensity score overlapping region which is also commonly referred to as the region of common support is shown in Figure 2.1. Only 111 and 181 households among the adopters and non-adopters of improved fallows met the overlap condition and were thus used in the matching.

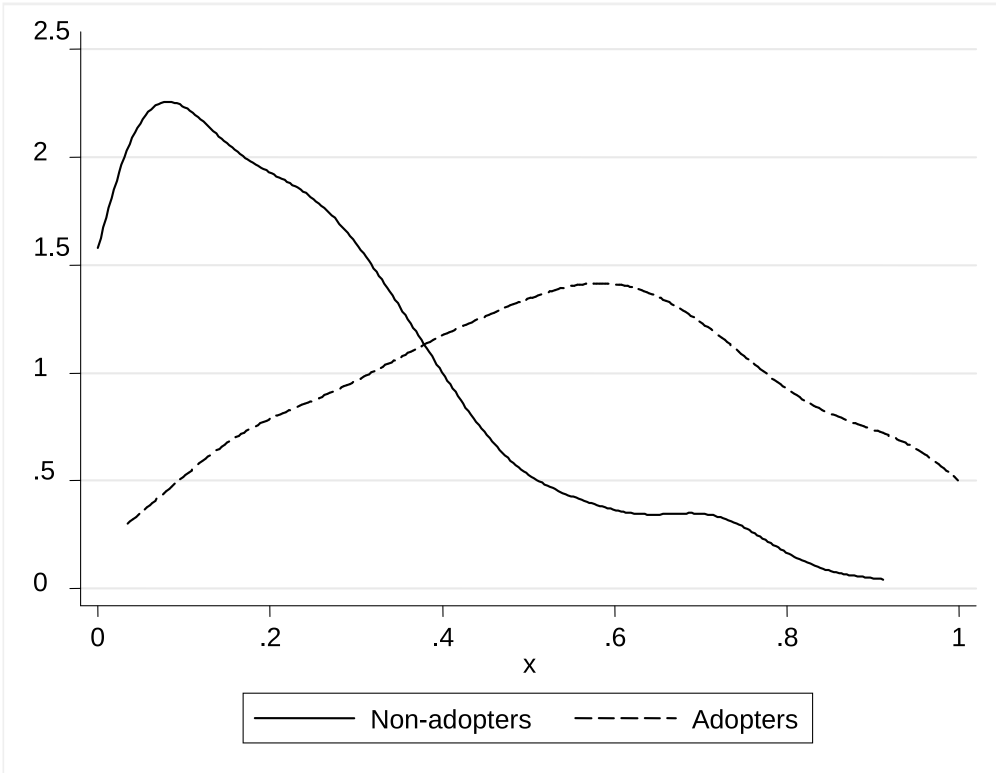

Figure 2.1: Distribution of the density of propensity scores showing Region of Common Support

Table 2.4: 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)
TLU[3]	Total Livestock Units	8.67 (0.861)***	3.48 (0.434)	5.26 (0.432)
Bicycles	Number of bicycles owned	1.26 (0.085)**	0.96 (0.047)	1.07 (0.045)
Radios	Number of radios owned	1.11 (0.067)**	0.93 (0.047)	0.99 (0.039)
OwnironRf	1 if farmer own iron roofed house, 0 otherwise	0.76 (0.041)**	0.49 (0.034)	0.58 (0.027)

*, **, *** 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]A TLU (Tropical Livestock Unit) is an animal unit that represents an animal of 250 kg liveweight, and used to aggregate different species and classes of livestock as follows: Bullock :1.25; cattle: 1.0; goat, sheep and pig: 0.1; guinea fowl, chicken and duck: 0.04 and turkey: 0.05 (compiled after Janke 1982).

Matching results are reported in Table 2.5 for the nearest neighbour method and Table 2.6 for the kernel matching approach. The nearest neighbour strategy used 56 households among the control units to match against 111 adopting households. Using the nearest neighbour 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 and maize yields per hectare.. The technology did not have a significant impact on per capita value of crop produced, crop income and the number of months in a year the household had enough own grown food for consumption (Table 2.5).

Table 2.5: ATT estimation of various outcome variables using Nearest Neighbour Method

	Average Treatment on Treated(ATT)	Standard Error	t value
[2]Value Crop Produce per MEU (ZK, 000)	256	214	1.195
Crop Income per MEU (ZK, 000)	135	257	0.524
Maize Income per MEU (ZK, 000)	320	168	1.908
Total Maize yield (tons)	1.013	0.542	1.868
Maize yield per MEU (tons)	0.380	0.137	2.771
Maize yield (ton/ha)	0.466	0.213	2.185
Months per year with enough grown food	0.414	0.550	0.753

Number of treated units used =111 and number of control units used = 56
[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 (181) to match against the 111 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 except per capita value of crop produce and crop income. 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 (Table 2.6).

Table 2.6: ATT estimation of various outcome variables using Kernel Matching

	Average Treatment on Treated (ATT)	Standard Error	t value
[2]Value Crop Produce per MEU (ZK, 000)	250	185	1.355
Crop Income per MEU (ZK, 000)	179	214	0.835
Maize Income per MEU (ZK, 000)	313	151	2.075
Total Maize yield (tons)	1.039	0.353	2.943
Maize yield per MEU (tons)	0.319	0.117	2.737
Maize yield (ton/ha)	0.532	0.201	2.651
Months per year with enough grown food	0.651	0.352	1.849

Number of treated units used = 111 and number control units used = 181
[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 balancing tests indicated that matching was successful since variables' biases that existed before matching between the adopters and non adopters were significantly reduced. After matching all the variables used did not portray any statistical difference between the adopters and the non adopters of improved fallows (Table A2.2, Appendix 1)

2.8.4 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 A2.3 to A2.7 in the Appendix 1. 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 lower 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 2.7. 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 2.7). 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.

Table 2.7: 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	811,334 (47941)	495,628 (36237)	315,707 (44637)***
Non-adopters	933,398 (40865)	317,301 (23921)	616,096 (36862)***
Heterogeneity effects	BH_1 = -122,064	BH_2 = 178,327	TH = -300,389
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	2.21 (0.049)	1.60 (0.034)	0.65 (0.051)***
Non-adopters	2.43 (0.043)	1.51 (0.024)	0.92 (0.046)***
Heterogeneity effects	BH_1 = -0.22	BH_2 = 0.13	TH = -0.27

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)

2.9 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 randomisation 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 analysing 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 value of crop produce, 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 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 emphasised.

However the findings from both kernel and nearest neighbour matching strategies on the impact of the technology on crop income (and value of crop produce) per capita were found to be 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 some of the high value crops can fairly do well on the soils improved by the technology after maize cropping. Farmers elsewhere have been planting cotton two years after the cropping of maize in former improved fallow plots (Katanga *et al*. 2007). In the improved fallow system the main crop grown after the fallow is maize. This is because maize is responsive to nitrogen application. Katanga *et al*. 2007 reveals that some farmers grew cotton after the residual effect of the fallows start going down, usually after two or three years of cropping maize. Cotton unlike maize is deep-rooted and might capture the nutrients that were leached to deeper layers. Research results have shown that with time, some nutrients from the improved fallow system will be leached to deeper layers (Chintu *et al*. 2003). According to Katanga *et al*. (2007), the yield of cotton after two years of maize after improved fallows was 1.3 tons per hectare. This was not statistically different from the cotton yields obtained from fully fertilized cotton crop.There might be need to sensitise farmers on the need to grow high value crops on improved fallow plots as well especially after one or two seasons of maize cropping when some of the nitrogen from the fallows have been used by maize.

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 500 - 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 500 - 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 analysing value of crop produce and 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 contextualised. 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, policies such as subsidies that directly target the maize crop or just that part of the maize crop emanating from the technology could have a more profound effect on adoption of the improved fallows than general crop or agricultural developmental support.

2.10 CONCLUSIONS

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 randomised 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 randomisation suggesting the need for researchers to adopt more robust evaluation methodologies in impact assessment of technologies.

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CHAPTER 3

ESTIMATING THE CAUSAL EFFECT OF IMPROVED FALLOWS ON ENVIRONMENTAL SERVICES PROVISION UNDER FARMERS FIELD CONDITIONS IN CHONGWE - ZAMBIA

ABSTRACT

The provision of environmental services on-farm by the improved fallow (an agroforestry technology) has largely remained empirically untested in Sub Saharan Africa including Zambia. Where effects of planting trees or agroforestry in general have been used to estimate the impacts on fuel wood consumption (hence mitigating deforestation), actual estimates of the size of fuel wood consumption changes have been lacking. We used data from a survey of 324 households in Chongwe district of Zambia to test the hypothesis that households embracing improved fallows use less fuel wood from the forest for their energy requirements since the technology provide wood as a by-product. Estimates from OLS regression, matching and endogenous switching regression showed that the technology had a significant causal effect on households' consumption of forest fuel wood. The technology can provide up to 1,086kg or about 51% of annual household fuel wood requirements in the year the fallows are terminated. We concluded that the technology has the capacity to provide environmental services under farmers' field conditions. In addition to promoting it for soil fertility improvement, the extension messages should explicitly reflect the technology's potential to provide on farm environmental quality.

Key words: Forest protection, fuel wood, matching strategies

3.1 INTRODUCTION

The increasing poverty levels among most small scale farmers in Sub-Saharan Africa offers the greatest developmental challenge on how best to balance the seemingly conflicting goals of agricultural production and environmental stewardship. To ensure an adequate livelihood, prioritisation of food security over the concern for sustainable environmental management has taken centre stage. However, there exist agricultural land use practices that produce multiple outputs that offer potential opportunities for achieving the two seemingly polarised objectives (Ajayi, *et al*. 2007). One such practice is the improved fallow technology. According to Böhringer (2002), improved fallows are fast-growing leguminous nitrogen-fixing woody trees or shrubs that are deliberately planted to grow on a field for a minimum of two years to ensure rapid replenishment of soil fertility. The improved fallows, developed and promoted by the World Agroforestry Centre (formerly, the International Centre for Research in Agroforestry) in most parts of Sub-Saharan Africa since the late 1988 serve to achieve objectives of natural fallows within a shorter time or a smaller area (Cooper, *et al.* 1996; Szott, *et al.* 1999). The main species used as improved fallows in Zambia and many parts of Sub-Saharan Africa include; *Gliricidia sepium* (Mexican lilac), *Cajanus cajan* (Pigeon pea), *Sesbania sesban* (River bean), *Tephrosia vogelii* (Fish bean) and *Faidherbia albida* (Winter thorn). After being cut, nutrients from the fallows support a crop (usually maize in most parts of the region) for 3 to 4 years without the application of any external inputs (Kwesiga, *et al*. 2003).

In addition to improving soil fertility levels, evidence suggests that improved fallows provide environmental services. According to literature, the technology generates several environmental services (Sileshi, *et al*. 2007) such as carbon sequestering (Kaonga & Bayliss-Smith, 2009; Makumba, *et al*. 2007), improvement of biodiversity (Sileshi, *et al*. 2007), mitigating deforestation through provision of fuel wood (Mafongoya & Kuntashula, 2005) and improvement of soil physical structure (Chirwa, *et al*. 2007). Although there are several studies (that we review below) that have generally linked on-farm tree planting to households' consumption of fuel wood, we note that the specific evaluation of the environmental impacts of improved fallows in Sub-Saharan Africa has rarely incorporated the socioeconomic circumstances of farmers. To the best of our knowledge, empirical evidence that takes into account the inter-linkages that exist between the socioeconomic conditions of farmers and the improved fallows' provision of environmental services are very few. Moreover extant literature (Govere, 2002; Ndayambaje & Mohren, 2011; Pattanayak & Depro, 2004) on the environmental impacts of improved fallows or agroforestry in general under farmer field conditions suggest employment of methods that would give precise causal effects estimates of the technology. Consequently, the purpose of this study was to estimate in a much precise way the potential impact of improved fallows on environmental service provision under farmers' field conditions using well designed quasi experiments.

We noted above that improved fallows can potentially produce multiple environmental services. However estimating the value of many of these services under farmer field conditions is potentially costly and scientifically challenging considering that with the exception of a few (e.g. fuel wood supply), most are not easily quantifiable. For instance it would be very costly to randomly and accurately measure the soil erosion or carbon sequestration benefits across farms planted with improved fallows. Likewise relying on farmer perception estimates on soil erosion or carbon sequestration benefits across farms planted with improved fallows might produce contestable scientific results. Although the primary objective of adopting improved fallows is soil fertility replenishment, the technology also co-produces fuel wood that adopting farmers use, and thus help in reducing deforestation. It is relatively much easier to compare public fuel wood consumption between adopters and non-adopters of improved fallows and attempt to estimate how much of this difference could be attributable to the technology.

Our decision to use fuel wood consumption as the outcome variable in estimating the causal effects of improved fallows on environmental services provision under farmer field conditions was made through informed consideration. Several economic studies and reviews of household fuel wood demand and supply in developing countries exists (Arnold, *et al*. 2006; Bardhan, *et al.* 2001; Cooke, *et al*. 2008; Kohlin & Parks, 2001; Patel, *et al*. 1995; Sills, *et al.* 2003). Typically the studies involve the estimation of fuel wood quantity and collection time. A number of these studies (Kohlin & Parks, 2001; Patel, *et al*. 1995; Pattanayak & Depro, 2004) use multivariate econometric analyses that generally include tree planting as one of the explanatory variables. Most of the coefficients of the tree planting dummy are negative validating the contribution of trees to reduced public forest fuel wood demand. However in all the reviewed literature a more precise estimate of how much of the forest wood is replaced by planted trees or agroforestry is lacking. Collectively, the studies on fuel wood show that household fuel wood consumption can easily (relatively) be estimated. Then fuel wood consumption between adopters and non-adopters of improved fallows could be compared.

In addition, the economic and environmental impacts of fuel wood can not be overemphasised. The World Resources Institute (WRI, 2000) estimates that fuel wood consumption accounts for about 15% of the primary energy supply in developing countries and provides up to 80% of total energy in some countries. It is the primary energy source for most poor rural households (Trossero, 2002; Mercer & Soussan, 1992) and thus an important factor in forest degradation. FAO (2010) estimates that in parts of Africa, fuel wood which is often the only domestically available and affordable source of energy, accounts for almost 90% of primary energy consumption. There is currently a shortage of fuel wood in Zambia and yet according to Chidumayo (2002) urban demand for fuel wood and charcoal has increased, and is said to be the major cause of deforestation in the country.

Chongwe district in Zambia, the site for the present study, provides a good example for policy to understand and evaluate the causal effect of provisioning environmental services (here, fuel wood collected from improved fallows) under farmer field conditions. To begin with, Kasisi Agricultural Training Centre (KATC), a quasi public institution mandated to promote good practice agriculture, has massively promoted improved fallows in the district since the late 1990s. In addition, deforestation in the district has of late been on the up swing partly due to its proximity location (about 30km) to Lusaka, the capital city of Zambia. Most urban Lusaka dwellers rely on charcoal for their cooking energy requirements, with most of the charcoal coming from Chongwe district. Recently there have been calls by government officials (GRZ 2012) to re-introduce trees and shrubs into existing cropland and to manage them systematically, so as to obtain fuel wood as well as to address land degradation problems. In this paper we seek to answer the question: is it necessarily true that the success of improved fallows in supplying fuel wood in on-station trials can be replicated under farmer field conditions to levels where deforestation rates will significantly decline?

Published studies on the environmental performance of improved fallows (Chirwa, *et al.* 1997; Kaonga & Bayliss-Smith, 2009; Mafongoya & Kuntashula, 2005; Makumba, *et al*. 2007; Sileshi, *et al*. 2007) mostly relied on data sourced from on-station and researcher managed on farm experiments. It is generally costly and complex to carry out randomised environmental measurements across several farms, thus most researchers resort to using quasi experiments on data obtained from real life situations. The goal of such experiments is to control for confounding factors in the estimation of impact of the technology. Our search has yielded scanty literature on the use of proper identification methods in isolating the role of improved fallows on environmental performance under farmer socioeconomic conditions.

Pattanayak and Depro (2004) used farm level data from the Manggarai region of Indonesia to estimate the impact of agroforestry on fuel wood consumption and soil erosion prevention. The study found that agroforestry reduced the collection of fuel wood from forests and that prevention of soil erosion depended on the type of agroforestry practised. While the role of confounding factors in affecting both soil erosion and fuel wood consumption outcome variables was accounted through multivariate ordered probit regressions, the study acknowledged the superior ability of robust methodologies such as matching or instrumental variables approaches in addressing potential endogeneity of the adoption choice. For Sub Saharan Africa where improved fallows have been promoted since the late 1980s, we found only one published review article (Ndayambaje & Mohren, 2011) on the role of agroforestry in fuel wood demand and supply in Rwanda. Although this article suggests that the demand for fuel wood is partly supplied by agroforestry systems, it does not quantify how much of fuel wood is supplied by the systems. Unpublished work on improved fallows and natural miombo woodland use in eastern Zambia by Govere (2002) applied descriptive analysis (t tests) and concluded that adopters consumed less fuel wood from the miombo forests than the non-adopters. Technology impact evaluation without accounting for confounding factors may lead to evidence that could mislead policy. It is difficult to attribute the changes in outcome variables to technology adoption alone if confounding factors that could have also influenced the outcome are not taken into consideration. Thus controlling for confounding factors in the process of evaluating impact of technologies becomes very pertinent.

In this study we contribute to the literature on on-farm environmental performance of improved fallows in two ways; first, since the literature is noticeably thin with respect to economic modelling of environmental services from improved fallows under farmers' field conditions, we attempt to partly fill this void. The studies reviewed above on the impacts of the improved fallow or agroforestry on on-farm environments could have not have succeeded in comparing similar groups of adopters and non-adopters as argued above. It follows that these studies most likely could have produced over or under identifiable causal effect estimates. In other words, the studies might have failed to explicitly explain the counter factual analysis so as to properly isolate the causal effect of the technology. This study used matching impact evaluation and endogenous switching regression techniques in estimating the causal effect of improved fallows on environmental performance under farmers' field conditions. Second, since most studies used binary or categorical responses to argue for the case of tree planting in general or agroforestry in particular; in reducing forest fuel wood demand, we attempt to provide more precise estimates of the actual size of forest fuel wood consumption changes that could be attributed to improved fallows. We hypothesised that households embracing improved fallows in Chongwe district would collect less fuel wood from forests for their energy requirements, since the technology provide wood as a by-product. Analysing farm-level data collected in 2011 from a random cross-section sample of 324 small-scale farmers revealed that improved fallows can significantly supply household fuel wood requirements.

Chapter 3 is structured as follows: discussions on analytical frameworks on households' production of environmental services, OLS regression, propensity matching and endogenous switching regression in this order follow the introduction. The study area, sampling design, survey instrument development and implementation complete the section on methodology. This is followed by the results and discussion section. Finally conclusions are drawn based on the findings of the study.

3.2 METHODOLOGY

3.2.1 Theoretical and analytical frameworks

3.2.1.1 Farmer production of environmental services from improved fallows

The production of environmental services through improved fallows was viewed as part of the many deliberate activities that a farmer engages in to maximise over all utility on the farm. The study considered an agricultural household model where farmer decisions in a given period were assumed to be derived from the maximisation of expected utility subject to land, labour, credit and other constraints such as materials used to have a successful improved fallow stand. Expected utility or profit was considered as a function of the farmer's choices of crops and the discrete choice to select the improved fallow from a mix of technologies in each time period. Detailed modeling of a typical farmer who maximises utility derived from income and environmental services from a technology such as improved fallows can be found in Pattanayak and Depro (2004).

The primary objective of adopting improved fallows is soil fertility improvement that would boost crop production. The environmental service such as fuel wood production comes as secondary benefit. Allocation of resources including those used in the production of the improved fallows are done in such a way that the marginal opportunity costs are equal to the marginal utility of consumption generated by that resource. The marginal utility of consuming privately produced fuel wood can also be equated to the marginal opportunity costs incurred in the collection of fuel wood from the public forests. The conceptual framework on the adoption of improved fallows has been discussed in detail in section 2.2.1 of Chapter 2.

3.2.1.2 OLS regression and propensity score matching techniques

First, we performed an ordinary least squares (OLS) regression analysis where the quantity of fuel wood consumed was assumed to depend on whether the household had adopted improved fallows or not while controlling for other confounding influences. The OLS model used was specified as:

$$Y_i = \alpha + \beta_i X_i + \mu_i \qquad (1)$$

Where; Y_i is the quantity of fuel wood consumed, Xi is a vector representing improved fallows as well as the other confounding factors, α is a constant and β_i are unknown parameters to be estimated that represent marginal and separate effects of the regressors while μ_i is the unobserved error term. A detailed review of this model and its accompanying assumptions can be found in Greene (2003).

Among the confounding factors that could influence quantity of fuel wood consumed included the age of the household head (more young and energetic heads could fetch more fuel wood from the forest), education (literate household heads could easily seek for alternative energy sources hence reduce demand on forest fuel wood), marital status and sex of head (for instance single or female headed households could find it difficult to gather a lot of fuel wood). Other factors considered were whether households were using oxcarts for fuel wood transportation, households total income that could make them use alternative energy sources, farm size and fallowed land that could provide fuel wood within the home stead, effective household size and consumption equivalent units that could increase labour for gathering fuel wood and energy requirements respectively, distance to forests that could increase time required to bring fuel wood to home stead and the camp dummy variables.

Second, we performed a more precise causal effect estimation of the improved fallows on the quantity of fuel wood consumed through the use of matching identification strategies. We used the potential outcome framework for causal inference discussed by Rubin (1974) which estimates the Average Treatment effect on the Treated (ATT) as:

$$E(Y_1 - Y_0) \mid T = 1 \qquad (2)$$

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

$$Y_0 \amalg T \mid (X) \qquad (3)$$

Besides the CIA, a further requirement for identification is the common support or overlap condition, which ensures that for each adopting household there are non-adopting households with the same observables. With these two assumptions, within each cell defined by *X*, adoption of improved fallows is random, and the outcome of non-adopting households can be used to estimate the counter factual outcome of the adopting households in the case of no treatment (Nannicini, 2007).

The matching estimation was implemented using the propensity score which is the conditional probability of adopting the improved fallow technology (Heckman, *et al*. 1998). The Propensity Score is usually unknown and this study estimated it through a probit regression in which the dependent variable equalled one if the household adopted improved fallows and zero otherwise. This was followed by checking the balancing properties of the propensity scores. Various specifications of the probit model based on the empirical model discussed in section 2......were attempted until the most complete and robust specification that satisfied the balancing tests was obtained. To provide for robustness check within the matching strategies, we implemented nearest neighbour with replacement and kernel matching techniques whose advantages and disadvantages can be reviewed in Caliendo and Kopeinig (2005). Stata version 11 was used to run the matching algorithms.

3.2.1.3 Endogenous switching regression

We used the Loksin and Sajaia (2004) specification of the endogenous switching regression model to control for unobservable covariates and check for robustness of the matching results. The criterion function or selection equation facing the households in the adoption of improved fallow was defined as;

$$I_i^* = \beta X_i + \alpha Z_i + \mu_i \qquad \text{with} \quad I_i = \begin{cases} 1 & if\ I_i^* > 1 \\ 0 & otherwise \end{cases} \tag{4}$$

where I_i^* is the unobservable variable for technology adoption and I_i is its observable counterpart, which equals one if the household adopts the technology and zero otherwise. β and α are vectors of parameters while X_i are vectors of exogenous variables such as age, education level, marital status etc. also included in output equations 5 and 6. Z_i are non-stochastic vectors of variables that explain only the selection process determining adoption and μ_i is random disturbances associated with the adoption of improved fallows. The variables that form Z_i are those that are highly correlated with the treatment variable but can not directly influence the outcome variable. For the fuel wood consumption model, total fertiliser use and the predominant soils being sand on the farm were highly correlated with adoption of improved fallows but were not correlated with the consumption of fuel would. These variables were used as Z_i.

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

Regime 1: $y_{1i} = \beta X_{1i} + \varepsilon_{1i}$ if $I_i = 1$ (5)

Regime 2: $y_{2i} = \beta X_{2i} + \varepsilon_{2i}$ if $I_i = 0$ (6)

where Y_{ji} are the dependent or outcome variables, in this case fuel wood 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 endogenous switching regression model can efficiently be estimated using the full information maximum likelihood (FIML) estimation (Lokshin and Sajaia, 2004). Assumptions accompanying this estimation and conditional expectations are fully given in Chapter 2. The FIML estimates of the parameters of the endogenous switching regression model were obtained using the STATA command *movestay* proposed by Lokshin and Sajaia (2004).

3.2.2 Study area

Although promoted through out Zambia, most research and development activities related to agroforestry have mainly been conducted in Chipata district of eastern Zambia and Chongwe district of Lusaka province. In Chipata district, the main organisation promoting agroforestry was the World Agroforestry Centre (WAC). Since the late 2000, WAC significantly scaled down agroforestry research and development in eastern Zambia as a result of diminishing funding. In Chongwe district, Kasisi Agricultural Training Centre (KATC) is the main organisation promoting agroforestry in the form of improved fallows. The scaling down of agroforestry activities in eastern Zambia, and the continued promotion of agroforestry by KATC in Chongwe district led to the later being purposively selected as the study area for this case study. The location of the district is shown in Figure 1. Informal interviews specifically designed to plan for plan for the study and identify areas where agroforestry is most concentrated in the district were held with extension officers from KATC. Three (out of 28) agricultural camps namely Nyangwena, Chinkuli and Katoba were identified as the main catchment areas with farmers practising improved fallows, and were targeted for the study. Generally, farmers in the catchment areas mainly grow the staple maize crop for food and sale. They also grow annual cash crops such as groundnuts, cotton and beans. Vegetable production involving rape, cabbage, tomato and onion in seasonally waterlogged wetlands is also common. The most common animals reared include cattle, chickens and goats.

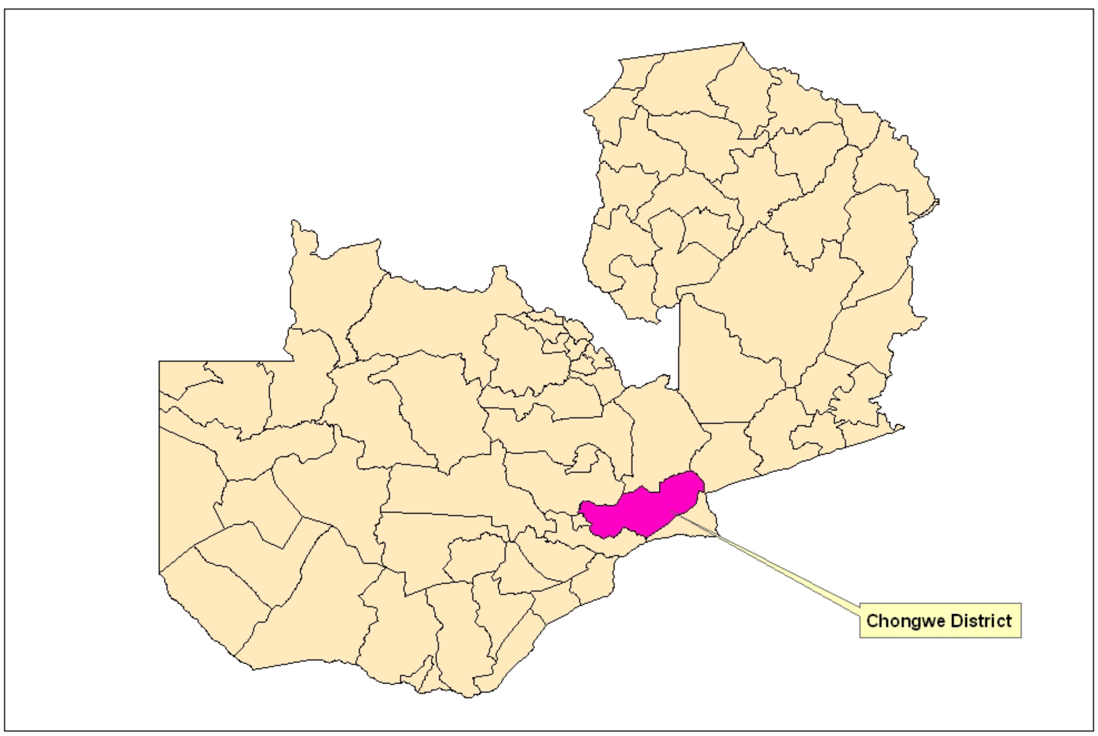

Figure 3.2: Map of Zambia showing the location of the study area

3.2.3 Sampling

The study used agricultural camp lists compiled by the Zambia Ministry of Agriculture camp extension officers to come up with a sampling frame. The lists from the three camps (catchment areas) were consolidated into one. Although we considered the samples drawn from the three camps as homogenous at this stage (hence consolidation into one list), the analysis to follow incorporated the heterogeneous effects of the camps. The sampling frame was then stratified between adopters and non-adopters of improved fallows. The sampling frame had a total of 7,081households of which approximately 20% were adopters of improved fallows. Due to limited logistics, the study aimed at interviewing around 5% (335 households) of the total households in the sampling frame.

Since matching strategies, one of the methodologies used in this study, require treatment or adopting units to have a larger pool of control or non-adopting units from which matches can be obtained (Caliendo & Kopeinig, 2005), the sample was stratified into 2:3 ratios for adopters and non-adopters respectively. It follows that from a stratum of 1,416 listed households using improved fallows, 134 were randomly selected using Stata (Stata version 11.2, 2009). Similarly, from 5,665 listed households, 201 non-adopters were randomly selected. Eventually due to non-responses, 130 adopting and 194 non-adopting households were interviewed. For the household to experience consumption of fuel wood from improved fallows, it should have harvested at least a fallow. The minimum period for improved fallow maturity in the study area was 2 years. Since this study was carried out at the end of 2011, a household should have planted improved fallows not later than 2009 to qualify as an adopter who could potentially influence consumption of fuel wood collected from forests. In addition, since our interest was to include only those households most likely to reap substantial benefits from consuming fuel wood harvested from improved fallows, our sample only included households that have been growing at least a quarter of a hectare under improved fallows. Using these criteria, 14 households using improved fallows dropped out from the - 130 that were in the original adoption category. These were added to the non-adopters category at the results analytical stage. As a result, the final sample used in the analysis was composed of 116 adopters and 208 non-adopters. Notwithstanding the above categorisation of adopters and non-adopters, we also run two additional sets of models in which the 14 households were either included in the adoption category (since they had shown intention to adopt) or were entirely dropped from the sample. These sets' results are relegated to the appendix. Since the probability of selection differed between adopters and non-adopters, we adjusted our standard errors by weighting our analyses through the inclusion of the probabilities of being selected in the two strata i.e. the probability of being selected was equal to N/n where N represented total adopters (non-adopters) of improved fallows and n, the actual samples selected.

3.2.4 Survey instrument development, pre-testing and implementation

We informally interviewed officers at Kasisi Agricultural Training Centre, agricultural camp extension officers and some lead farmers 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 interviews and a review of literature, a structured formal questionnaire was drafted. The questionnaire went through several refinements following interactions between the authors. The final version of the questionnaire particularly useful for this specific study covered four main sections. The first section covered the basic households' demographic and socioeconomic characteristics. The second section explored the asset levels of households and use of improved fallows. The third section assessed general agricultural practices in the study area such as agricultural related challenges; types and amounts of inputs used and crop production levels. The final part looked at issues related to environmental impacts of the improved fallows such as households' fuel wood consumption.

Before the formal survey, a pre-test study comprising 16 households was carried out in the study area in October 2011. The pre-test survey served two purposes; firstly, the study wanted to ensure that the questionnaire had questions that were well understood by farmers, questions were logically flowing, and the interviewer could clearly understand the responses given by farmers. Secondly, the pre-testing provided the opportunity to practically train the research assistants on how best to implement the survey and measure the key outcome variable: household fuel wood consumption. The household fuel wood consumption variable was a combination of both researcher measured and farmer self reporting data. The steps involved in measuring this variable involved the following:

Step 1: Usually, the household head (main respondent) would take the enumerator to where the household stored fuel wood. The quantity of fuel wood found was measured using a hanging scale. Using the fuel wood found, the head would be asked how much of such fuel wood they consume in a month. This gave us the monthly quantity consumed by the household regardless of their improved fallow adoption status. This monthly estimate was multiplied by 12 months to give us the amount of annual fuel wood used by a household.

Step 2: This step involved establishing how much fuel wood was consumed from improved fallows by the adopters so that necessary adjustments could be made on their annual fuel wood consumption demand. Since the adopters could not clearly remember the quantities of fuel wood from the technology at fallow termination we went round this problem by asking the adopters to estimate how long in a year they had used fuel wood from improved fallows after fallow termination. They were further asked if they ever exchange through selling or bartering with neighbours the improved fallow fuel wood. All adopting households confirmed they never sold wood, they used it for own-consumption. The annual estimate for the adopting households was adjusted by the average number of months during which they were consuming fuel wood from the improved fallows. Since most households indicated that they cut improved fallows every 2 years, we emphasise that the estimated causal effects figures are obtained in year the household terminate the fallow.

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 in November and December 2011. The three camp extension officers from the catchment areas and an officer from Kasisi Agricultural Training Centre in Chongwe assisted in both the pre-testing and final implementation of the survey.

3.3 RESULTS AND DISCUSSIONS

3.3.1 Socioeconomic characteristics of the sample households

Socioeconomic characteristics of the household heads involved in the study are shown in Table 3.1. There was no significant difference in the average age of adopters and non-adopters of improved fallows. For the whole sample, the average age of the surveyed household heads was about 46.4 years. There was a significant difference in the average active family labour force between the adopters (4.6 persons) and non-adopters (3.8 persons). The sample was dominated by male headed households with no significant 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 compared to non adopters, had large farm sizes, cropped land as well as land put to maize production in 2010/2011 season (Table 3.1).

Table 3.1: Households fuel wood consumption and socioeconomic characteristics of farmers in Chongwe district, Zambia

	Overall (N = 324)	Adopters (N = 116)	Non adopters (N = 208)	$P > T\ (X^2)$
Public Fuel wood demand (kg/yr)	2127 (81.9)	1743[1] (109.2)	2341 (109.6)	0.000
Age (years)	46.4 (0.735)	47.1 (0.780)	46.2 (0.976)	0.595
Household size (MEU)	3.9 (0.103)	4.6 (0.173)	3.8 (0.127)	0.001
Farmland size (ha)	3.6 (0.127)	5.1 (0.270)	3.3 (0.137)	0.000
Cropped land(ha)	2.4(0.082)	3.4 (0.170)	2.2 (0.090)	0.000
Cropped maize area (ha)	1.6 (0.064)	2.3 (0.128)	1.4 (0.072)	0.000
Improved fallow area (ha)	0.86 (0.049)	0.8 (0.046)	1.3 (0.673)	0.560
Gender (% households heads)				
Male	81.8	85.3	80.8	
Female	18.2	14.7	19.2	
$P > X^2$				0.255
Education (% households heads)				
Never been to school (1)	9.4	3.4	10.7	
Attended primary (2)	33.8	22.4	36.3	
Completed primary (3)	23.8	32.8	21.8	
Attended secondary (4)	27.4	29.3	27.0	
Completed secondary (5)	4.6	11.2	3.2	
Attended tertiary (6)	1.0	0.9	1.0	
$P > X^2$				0.001
Marital status (% households)				
Married (1 = yes, 0 otherwise)	82.1	84.5	81.7	
Single (1 = yes, 0 otherwise)	4.4	6.0	4.0	
Widow (1 = yes, 0 otherwise)	10.5	8.6	10.9	
Divorced (1 = yes, 0 otherwise)	2.9	0.9	3.4	
$P > X^2$				0.297

Figures in parentheses are standard errors of the mean

Man equivalent units (meu) were calculated following Runge-Metzger (1988) as: < 9 years = 0; 9 to 15 and over 49 years = 0.7; 16 to 49 = 1.

[1]fuel demand the year the adopters terminate the fallows. Common practice is that farmers' terminate fallows every other year.

3.3.2 Improved fallows and the consumption of fuel wood from forests

There was a significant difference at 95% confidence level between adopters and non-adopters of improved fallows in the average number of times per month (3.6 versus 4.7 times respectively) they collected fuel wood from forests. This was despite the average monthly weight of fuel wood collected from the forest being statistically the same (adopters = 84.3kgs and non-adopters = 80.7kgs). It was estimated from adopters of improved fallows who had cut their improved fallows in 2011 that they spent on average 1.56 months annually using fuel wood from the technology. Therefore while non-adopters consumed forest wood for the entire 12 months period in a year, adopters consumed forest wood for 10.44 months. The monthly fuel wood demand estimates were multiplied by these factors to come up with the annual estimates that were used in the later analysis.

3.3.3 OLS regression estimates

Results on OLS regression of the effects of adoption of improved fallows on fuel wood consumption are shown in Table 3.2 (also see Tables A3.1 and A3.2 in Appendix 2). The estimates showed that consumption of forest fuel wood is negatively correlated with on-farm planting of improved fallows. Almost 846 kgs of forest fuel wood would be replaced by improved fallows assuming all adopters terminated the fallows in that particular year. The other striking result from the estimates was that while farm size was positively significantly correlated with consumption of forest fuel wood, the amount of land reserved as fallow had a negative correlation which was not significant. Fallowed land usually provides some tree shrubs (depending on the period of fallowing) and these serve as an alternative source of fuel wood.

Table 3.2: OLS regression results with 14 farmers with intent to adopt omitted from the adopters category

	Coefficient	Standard errors	t statistic
IF2009	-845.9***	187.0	-4.52
HHage	10.07	6.838	1.47
HHedu	35.28	75.04	0.47
Marr	-120.6	396.4	-0.30
Wid	19.92	438.8	0.05
Divor	-975.3*	577.2	-1.69
MaleHH	196.8	287.4	0.68
CEU	6.796	72.23	0.09
HsizeE	30.49	84.95	0.36
TotIncome (K,000)	2340	164	0.14
DistFW	-76.77	80.39	-0.95
Farmsi	92.36*	54.69	1.69
AreaFa	-101.8	73.41	-1.39
Oxcarts	270.8*	141.0	1.92
Chainda	-456.1**	218.9	-2.08
Katoba	831.1***	222.2	3.74
Constant	1,317**	551.8	2.39
Observations	323		
R-squared	0.218		

Standard errors in parentheses
*, **, *** significant difference between adopters and non-adopters means at 90%, 95% and 99% confidence levels
[1] for variable descriptions see Table 3.3

3.3.4 Propensity score matching estimates

The descriptions of the variables used in estimating the propensity score model are shown in Table 3.3. The choice of the variables was based on an extensive literature review and various model fitting attempts.

Table 3.3: Descriptive statistics of selected variables used in various models and in estimating the propensity score

Variable	Definition	Adopters (N = 116)	Non-adopters (N = 208)	Over all (N = 324)
HHage	Age of household head (years)	47.3 (0.801)	46.5 (0.963)	46.7 (0.690)
MaleHH	1 if household head is male, 0 otherwise	1.15 (0.034)	1.19 (0.027)	1.18 (0.021)
HHedu	Years of formal education of household head (categories 1-6)[1]	3.25 (0.103)*	2.75 (0.075)	2.95 (0.062)
Marr	(1 = if household head is married, 0 otherwise)	0.84 (0.034)	0.82 (0.027)	0.82 (0.213)
Sing	(1 = if household head is single, 0 otherwise)	0.06 (0.022)	0.04 (0.014)	0.04(0.011)
Wid	(1 = if household head is widowed, 0 otherwise)	0.09 (0.026)	0.11 (0.022)	0.11 (0.017)
Divor	(1 = if household head is divorced, 0 otherwise)	0.01 (0.009)*	0.034 (0.012)	0.03 (0.009)
Logsize	Log of household members	1.43 (0.041)***	1.22 (0.034)	1.26 (0.027)
DistFW	Distance to fuel wood forest (1 = <1km, 2 = 1- 3Km, 3 = 3-5 km, 5 = >5km)	2.21 (0.099)**	1.87 (0.068)	1.93 (0.056)
CEU	Consumer equivalent units (< 9years = 0.4; 9 to 15 = 0.7; Males 16 to 49 = 1; Females16 to 49 = 0.9 and over 49 years = 0.8)	5.36 (0.199)*	4.79 (0.149)	4.89 (0.121)
AreaF	Size of fallowed land in 2011 in hectares	1.74 (0.192)*	1.02 (0.096)	1.15 (0.086)
Chainda	1 is the household is domiciled in Chainda, 0 otherwise	0.41 (0.046)*	0.31 (0.032)	0.32 (0.026)
Katoba	1 is the household is domiciled in Chainda, 0 otherwise	0.35 (0.044)	0.37 (0.033)	0.37 (0.027)
IF2009	Using of improved fallows 2009 and before (1 = yes, 0 = No)	-	-	0.18 (0.021)

*, **, *** significant difference between adopters and non-adopters means at 90%, 95% and 99% confidence levels

[1] see Table 3.1 for the definition of categories.

The propensity score (PS) estimation results are shown in Table 3.4. We tried out different model specifications while checking for the balancing properties of the propensity score. The specification used in this study satisfied the balancing procedure tests. Only matches whose distribution of the density of the propensity scores overlapped between the adopters (116 households) and non-adopters (168 households) observations were used in the matching algorithms. The distribution of the density of the propensity score overlapping region (common support region) is shown in Figure 3.

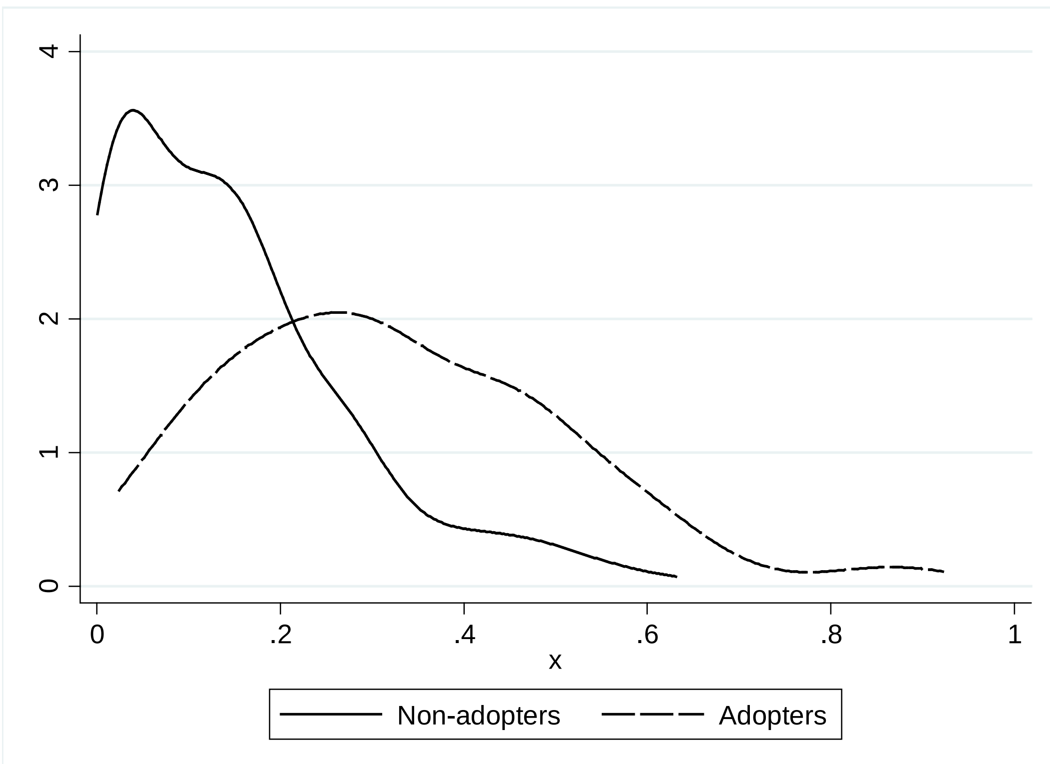

Figure 3.2: Distribution of the density of propensity scores showing Region of Common Support Fi

The variables household head age, age squared, single headed households, household membership size, distance to forest, being domicile in Chainda significantly influenced the estimation of the propensity score. Similar results were obtained in the models incorporating the 14 farmers with intent to adopt as part of the adopters or entirely dropping them from the sample (Table A3.3 and A3.4 in Appendix 2). The propensity scores were used to estimate the average adoption effects of improved fallows on the adopters with regards to fuel wood consumption.

Table 3.4: Estimation of propensity score probit results

Variable	Coefficient	Robust standard error	Z
HHage	0.219***	0.0542	4.04
HHedu	0.245	0.362	0.68
MaleHH	0.408	0.258	1.58
Marr	0.665	0.552	1.20
Sing	1.513**	0.639	2.37
Wid	0.844	0.601	1.40
Logsize	0.750**	0.315	2.38
HHage2	-0.00208***	0.000539	-3.86
HHedu2	-0.0206	0.0561	-0.37
DistFW	0.181**	0.0807	2.25
CEU	-0.0921	0.0657	-1.40
Chainda	0.321*	0.192	1.68
Katoba	0.214	0.201	1.06
Constant	-9.009***	1.493	-6.03
Observations	324		
Log pseudo likelihood	-130.93		
Wald chi2(13)	47.34		
Prob > chi2	0.0000		
Pseudo R^2	0.14		

Standard errors bootstrapped 1000 times
*, **, *** significant difference at 90%, 95% and 99% confidence levels

The causal-effect estimates of improved fallows on forest fuel wood dependence using both the nearest neighbour with replacement (NN) and kernel matching (KM) strategies are shown in Table 3.5 in the case were the farmers with intent to adopt were relegated to the non adoption category and Tables A3.5 and A3.6 in Appendix 3 for the two other sample selections. The NN strategy showed that the causal effect of the improved fallow technology on forest fuel wood consumption was about 430 kgs per household in 2011 (assuming all adopters terminated or harvested fallows this year). Since most adopting households in the study area harvested fallows at least every other year, it can be estimated that dependence on the forest for fuel wood reduces by approximately half of this amount annually. The KM strategy that used more observations to come up with a counter factual group also showed that the technology significantly contributed to households' provision of fuel wood. The causal effect estimate from this strategy was higher (580 kgs) than that from NN approach. As expected, since more observations were used, the standard error from the KM strategy was relatively lower than that from the NN strategy.

Table 3.5: ATT estimation of the causal effect of improved fallows on forest fuel wood (kg) with the Nearest Neighbour and Kernel Matching methods in Chongwe, Zambia

	Number of adopters	Number of non-adopters	Average treatment effect on the treated (ATT)	t value
Nearest neighbour matching	116	64	-430.2 (258.7)*	-1.663
Kernel matching	116	174	-580.1 (192.9)***	-3.006

*, **, *** significant difference at 90%, 95% and 99% confidence levels
Bootstrapped standard errors in parentheses with 1000 replication samples
The numbers of treated and controls refer to actual nearest neighbour (NN) matches. Only 64 non-adopting households could be matched with the adopters

Results when the 14 farmers with intent to adopt were included in the adoption category gave the causal effect estimates of -320 (NN) and -447 kgs (KM) of fuel wood the year the improved fallows are terminated. When the 14 farmers with intent to adopt are dropped from the sample the NN strategy showed that the causal effect of improved fallows on forest fuel wood consumption was -434 kg. The KM strategy showed that the technology provided about -551 kg of fuel wood (Tables A3.5 and A3.6 in Appendix 3).

The post matching tests showed that matching was successful in all the models. Before matching the variables used had high degree of bias between the adopting and non-adopting categories in all the three models. During matching this bias was significantly reduced in all the variables used except and there was no statistical difference in all the used variables between the adopters and non-adopters. (Tables A3.7 – 3.9 in Appendix 4).

3.3.5 Endogenous switching regression model results

The full information maximum likelihood estimates of the endogenous switching regression model are reported in Tables A3.12 to A3.14 in Appendix 5. The first and second columns presents the estimated coefficients of the fuel wood functions for households that did and did not adopt improved fallows, while the third column presents the selection equation estimates on adopting improved fallows or not. To analyse the correlates of fuel wood consumption and improve on identification from unobservable factors, all the explanatory variables we had used in the propensity score estimation and two instruments (variables highly correlated with improved fallows but not directly related with fuel wood consumption) were included. The correlation coefficients (rhos) between the adoption and non-adoption functions and the selection equation were close to zero and non significant, in all the three models, suggesting non self selection in the adoption of improved fallows.

For 2011 and assuming that all adopters cut the improved fallows, the expected annual household fuel wood consumption under actual and counterfactual conditions are shown in Table 3.6. Predictions from the endogenous switching model show that adopters of improved fallows would statistically have used more fuel wood had they not adopted, while the non-adopters would have used less fuel wood from the forest had they adopted the technology. The predicted treatment effect on adopters and non-adopters was estimated at -1086 kgs and -426 kgs respectively, of fuel wood per household per every fallow termination year. Again just like for the matching estimates, these figures could be adjusted to half since most households terminated their fallows every after one year. The transitional heterogeneity effect is negative (less fuel wood) meaning that the effect is bigger for the adopting compared to the non-adopting households. This probably partly explains why the non-adopting households were not adopting in the first place.

Table 3.6: Average expected annual household fuel wood consumption (kg) for improved fallow adopters and non-adopters in Chongwe, Zambia using endogenous switching regression

	Decision stage			
	To adopt	Not to adopt	Treatment effect	t value
Adopters (N = 116)	1742.8 (62.6)	2828.8 (78.6)	-1086 (90.7)	-11.9693
Non-adopters (N = 208)[1]	2339.9 (53.9)	2765.5 (79.5)	-425.5 (86.8)	-4.9003
Heterogeneity effects	BH_1 = -597.1	BH_2 = 63.3	TH = -660.5	

[1]Fourteen (14) farmers with intent to adopt relegated to non-adoption category
*, **, *** significant difference at 90%, 95% and 99% confidence levels
The number in parentheses show standard errors
BH = the effect of base heterogeneity for households that adopted and those that did not
TH = transitional heterogeneity, the difference between the treatment effect on the treated or adopters (TT) and the treatment effect on the untreated or non-adopters (TU)

When the 14 farmers with intent to adopt were included in the adoption category, the treatment effect from the endogenous switching regression was -822 kg for the adopters and -173 for the non-adopters of fuel wood in the year the improved fallows are terminated. When the 14 farmers with intent to adopt are dropped from the sample the treatment effect or causal effect of improved fallows on forest fuel wood consumption was -1060 and -387 kg for adopters and non-adopters respectively (Tables A3.10 and A3.11 in Appendix 5).

Estimates from quasi-experiments are expected to approximate those you would get from well designed randomised experiments. This is because by controlling for confounding factors, there is a mimic of control plots in the randomised biophysical experiments. This study controlled for observable confounding factors through matching strategies and unobservables through endogenous switching regression. From the estimates, the maximum amount of fuel wood that the improved fallows can provide at fallow termination was about 1,086 kgs. This is about 51% of the annual fuel wood demand the year the fallow is terminated or half of this figure since the farmers in the study area terminated the fallows every after other year.

Considering that the average area of improved fallows per household in 2011 was almost one hectare (0.86 ha), a crude comparison with researcher managed trials could be made. Kwesiga *et al*., (1999) estimated that more than 10,000 kgs per hectare of fuel wood can be harvested from researcher designed and managed 2 – 3 years old improved fallows. Climate Management, a project promoting production of fuel wood from the *Cajanus cajan* improved fallows in the study area estimated that up to 7,000 kgs of fuel wood per hectare could be obtained from well managed and supervised two year old demonstration plots. This shows a huge disparity between what can be obtained on the farmers' fields and on professionally managed plots. Since the effects of confounding factors were only equalised between adopting and non-adopting farmers, and not between farmers and experimenters (demonstrators), it appears reasonable to attribute such differences to farmers' limited capacity to properly manage fallows.

Forty six households from the adopting category answered to the question on the disadvantages of improved fallows. The major disadvantages cited included labour intensiveness (cited by 43.5% of these households) and the long waiting period before benefits materialise (cited by 45.7% of the households). Some households (8.7%) cited the large land demand that the technology requires, while 2.2% mentioned that the improved fallow harbours pests and diseases. Household labour limitations and hence poor fallow management can directly contribute to the differences in fuel wood productivity between experimental and farmer managed plots. The long waiting period can indirectly affect these differences since more limited time would be competed between taking care of other farm activities and looking after the fallows. In either ways the optimal management of improved fallows on-farm would be compromised. Research into fast growing and wood producing short duration improved fallows need to be made part of the agenda of those involved in the promotion of improved fallows like KATC. Moreover, managing trees for soil fertility and wood production being a relatively new on-farm activity, farmers need to be continuously trained in tree management to help close the gap in improved fallow fuel wood yields between farmers and researchers.

3.3.6 Potential of improved fallows to protect the forests

Results from this study showed that there is a causal effect between adoption of improved fallows and household forest fuel wood demand. Although this case study was localised to a specific area, some crude conclusions could be made on the capacity of adopting farmers in protecting the public forests. The average area put under improved fallows in the study area stood at 0.86ha per household. Chidumayo (1997) estimated that Zambia loses about 200 000ha of forests per year. More recently the Zambian government officials at the Ministry of Environment and Tourism (GRZ, 2008) estimated that about 300 000 ha of forest is being cleared every year. Using the recent estimate (and 0.86 ha per household), it would require about 349,837 households putting part of their farms to improved fallows every year to counter this level of deforestation. Zambia currently has a population of 1.3 million households engaged in agriculture with relatively enough land (Musanya, 2011). Therefore meeting such a target is not far fetched as long as there is political will and concerted efforts in promoting the technology on-farm. Given that the Government of Zambia subsidises inorganic fertiliser to most resource poor small scale farmers (900,000 in 2011/12 farming season) through the Fertiliser Input Support Programme (Hichaambwa & Jayne, 2012), consideration towards tying these subsidies with the uptake of improved fallow could be an option. The technology will provide both, the much required improvement in soil fertility and protection of the public forests. Farmer investment in improved fallows could also be promoted through the explicit provision of extension messages that links the technology to environmental benefits such as the conservation of forests, in addition to the welfare contribution through crop production that is primarily the objective of the technology.

3.4 CONCLUSIONS

This study used simple, cost effective and more scientifically robust techniques to demonstrate the benefits of improved fallows in the provision of environmental services on farmers' fields. The study evaluated the potential impact of adopting improved fallows on on-farm environmental quality measured by the technology's contribution to fuel wood provision. The study utilised farm household level data collected in 2011 from a randomly selected sample of 324 households in Chongwe district of Zambia. Estimates from OLS regression, propensity score matching and endogenous switching regression showed that the technology has impact on household fuel wood consumption. Adoption of improved fallows reduced dependence on forests for fuel wood by up to 1,086 kgs at fallow termination, implying that less forest would be deforested. These results confirm the role of the improved fallow technology in improving on farm environmental quality.

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CHAPTER 4

GENERAL DISCUSSION, CONCLUSIONS AND RECOMMENDATIONS

Evaluation of agricultural technologies in sub Saharan Africa has for a long time suffered from inadequate tools to properly estimate both welfare and on farm environmental impact of such interventions. Most studies (see introduction chapter) on the impact of improved fallows on farmer welfare and on-farm environmental quality in Zambia and sub Saharan Africa have failed to account for selection bias in there estimation. In addition to selection bias problems, there has literally been a tendency by most researchers to use results from on-station randomised experiments to suggest that the improved fallows can equally provide environmental services under farmers' field conditions. The few studies that have attempted to link general on-farm tree planting to public forest wood products savings have not provided the actual quantities of how much wood products can be replaced.

In this study we deployed robust econometric analytical tools to properly isolate the causal effect of the improved fallows on farmer welfare and on-farm environmental quality. The study used nearest neighbour and kernel matching strategies to control for selection bias through observable covariates while endogenous switching regression was used to account for any endogeneity and selection bias due to unobservable factors.

The use of proper randomisation procedures (matching and endogenous switching regression) in the evaluation of the improved fallows demonstrated the importance of using the right tools in assessing technologies. Both matching and endogenous switching regression methods confirmed that improved fallows have a positive impact on farmer welfare through increased maize yield and maize income. Although significant differences in crop income and/or value of crop income existed between the adopters and non-adopters of the improved fallows, the robust methodologies showed that these differences were mainly stemming from other sources (including maize produced using other inputs) and not necessarily from the maize crop grown after the improved fallows. This implied that compared to other sources, maize income or indeed the value of maize from the improved fallows was not enough to exert significant influence on crop income. This calls for the technology's use to be extended to other cash crops that can have significant influence on crop income. Although there is need for the agronomic performance of cash crops such as cotton (that is common in the study area) on previous improved fallow fields to be investigated, there is some evidence provided in chapter 2's discussion section showing that elsewhere farmers have been growing cotton on former fallow plots two years after maize cropping. This was not the case for farmers who were cropping for the second or third time in the study area. Improved fallows supplies a lot of nitrogen hence it makes agronomic sense to immediately crop a high nitrogen demander crop such as maize immediately after fallow termination. The cash crops requiring less nitrogen can be planted after two years or so. Maize productivity from the improved fallow was also found to be much lower than from controlled randomised experiments suggesting that farmers' have not yet mastered how to manage the trees so that they can get full benefits. Thus training of farmers in tree management should be a continuous process among the farmers embracing the technology.

Generally, the estimates of the welfare effects of improved fallows were found to be lower when compared to estimates obtained from simple comparisons between adopters and non adopters using the non randomised conventional t tests. There have been high expectations of the adoptability of improved fallows among the resource poor farmers because of conventional impact assessment that appeared to indicate that the technology provided a lot of private welfare benefits. When other factors driving welfare were controlled for, the benefits were found to be lower. This shows that there is need to avoid over (or under) identification of the impact of a technology because this could mislead both researchers and policy makers into making wrong conclusions and recommendations altogether. When estimating impacts of technologies, more robust evaluation techniques that are readily adaptable as demonstrated in this study needs to be used. Given the foregoing discussion, the first null hypothesis stating '*the adaptation and use of matching and endogenous switching regression strategies in estimating the causal effects of* *improved fallows will provide similar welfare impact estimates as those provided by non randomised conventional impact methodologies'* is thus rejected. The study accepts the alternative hypothesis stating that '*the adaptation and use of matching and endogenous switching regression strategies in estimating the causal effects of improved fallows will provide lower welfare impact estimates than those provided by non randomised conventional impact methodologies.*

Again, through the use of matching strategies that control for selection bias through observable covariates and endogenous switching regression that account for non-observable factors, in addition to OLS regression, the study confirmed that the improved fallows provide on-farm environmental services by substitution of natural forests fuel wood with improved fallow fuel wood. Unlike a few other studies that only associated on-farm planting of trees with reduction in household public forest wood consumption, this study precisely estimated the technology's substitution effect. It was estimated that at fallow termination (which is done biannually in the study area) the technology could replace up to 1,086kg of public fuel wood per household per year. This is almost 51% of the total annual household fuel wood requirements. Therefore the technology is potentially capable of mitigating deforestation due to rural households' energy needs. Thus the hypothesis that "*farms embracing improved fallows will just be as likely as those not using the technology to be dependent on the natural forests for by-products that are provided by the technology such as fuel wood* is also rejected. Instead, the study accepts the alternative hypothesis stating that: *farms embracing improved fallows are less likely to be dependent on the natural forests for by-products that are provided by the technology such as fuel wood.*

Thus, adoption of the technology would therefore not only directly lead to improved food security as stated above but would also indirectly contribute towards increased production since it would reduce time taken to fetch fuel wood. Although these estimates are coming from a case study in one district of the country, the findings give a crude idea of how much substitution of natural forest wood would occur if more small scale farmers take up the improved fallow.

Moreover it is widely known that the wood products that contribute to most of the degradation of forest woodlands in Zambia and most sub Saharan Africa are fuel wood and timber.

The role of the improved fallows to remedy soil fertility has widely been accepted by the farmers in the study area. This is mainly because it has been promoted as such. Therefore the short term primary objective for farmers is to increase their private welfare through increased crop yields and income. Some work needs to be done to reshape this thinking so that the farmers not only regard the technology in terms of soil fertility enhancement but also the provision of wood (and non-wood) products that equally contribute to their welfare. The extension messages could explicitly reflect this in addition to the fact that the technology is environmentally sustaining.

In conclusion, the improved fallow provides positive impact on both farmer welfare and on-farm environmental quality. For the Chongwe farmers' better crop yields and income could be obtained if farmers can diversify the use of the technology on other crops and also improve in the management of the technology. Further on-farm evaluation studies on how the technology contributes to the other environmental services such as carbon sequestration, increased biodiversity and others need to be pursued.

APPENDICES

Appendix 1: Results of the propensity score estimation, matching balancing tests and full maximum switching regression

Table A2.1: Estimated propensity score results

Variables	Coefficient	Standard error	Z
HHage	0.179***	0.052	3.44
HHedu	0.168	0.419	0.40
MaleHH	0.102	0.325	0.31
HsizeE	0.049	0.048	1.04
Marr	0.602	0.679	0.88
Sing	1.444*	0.744	1.94
Wid	0.748	0.696	1.07
HHage2	-0.002***	0.001	-3.65
HHedu2	-0.017	0.065	-0.26
SoilfertCH	0.074	0.169	0.44
Farmsi	0.240***	0.049	4.95
TLU	0.027**	0.011	2.35
Bicycles	-0.027	0.116	-0.23
Radios	0.009	0.126	0.07
OwnironRf	0.256	0.191	1.34
Katoba	-0.001	0.204	-0.000
Nyangwena	-0.962***	0.251	-3.82
Constant	-6.755***	1.549	-4.36
Observations	324		
LR Chi2 (17)	109.63		
Prob > chi2	0.0000		
Pseudo R2	0.26		
Log likelihood	-153.43		

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

Table A2.2: Matching balancing tests for farmer welfare estimation models

		Mean Treated	Control	% bias	% reduction IbiasI	t-test t	p> t
HHage	Unmatched	47.27	46.47	6.9		0.55	0.583
	Matched	47.27	48.29	-8.8	-26.9	-0.82	0.413
HHedu	Unmatched	3.25	2.79	42.3		3.58	0.000
	Matched	3.25	3.25	0.6	98.5	0.05	0.962
MaleHH	Unmatched	0.85	0.81	10.4		0.87	0.382
	Matched	0.85	0.86	-4.1	60.3	-0.33	0.745
HsizeE	Unmatched	4.55	3.81	40.1		3.46	0.001
	Matched	4.55	5.04	-26.4	34.2	-1.41	0.161
Marr	Unmatched	0.84	0.82	5.5		0.47	0.640
	Matched	0.84	0.86	-4.6	16.2	-0.36	0.721
Sing	Unmatched	0.06	0.04	11.6		1.04	0.301
	Matched	0.06	0.06	3.7	68.6	0.25	0.804
Wid	Unmatched	0.09	0.11	-6.0		-0.50	0.615
	Matched	0.09	0.08	3.1	48.7	0.24	0.810
HHage2	Unmatched	2305.1	2356.2	-4.4		-0.35	0.728
	Matched	2305.1	2426.7	-10.4	-138.0	-0.98	0.328
HHedu2	Unmatched	11.74	9.01	39.4		3.41	0.001
	Matched	11.74	11.64	1.4	96.5	0.80	0.422
SoilfertCH	Unmatched	0.42	0.41	2.1		0.18	0.859
	Matched	0.42	0.42	1.0	51.1	0.07	0.941
Farmsi	Unmatched	5.16	3.25	76.9		7.02	0.000
	Matched	5.16	4.86	12.2	84.1	0.80	0.422
TLU	Unmatched	8.67	3.48	66.3		6.00	0.000
	Matched	8.67	9.01	-4.4	93.3	-0.24	0.807
Bicycles	Unmatched	1.26	0.96	36.4		3.20	0.002
	Matched	1.26	1.31	-5.4	85.5	-0.38	0.702
Radios	Unmatched	1.11	0.92	26.4		2.27	0.024
	Matched	1.11	1.08	3.8	85.5	0.28	0.779
OwnironRF	Unmatched	0.76	0.49	57.5		4.80	0.000
	Matched	0.76	0.75	0.8	98.6	0.06	0.951
Sample		Pseudo R2	LR chi2	P>chi2	Meanbias	Medbias	
	Raw	0.218	90.71	0.000	28.8	26.4	
	Matched	0.022	6.71	0.965	6.0	4.1	

Table A2.3: Full information maximum likelihood estimates of the switching regression model – crop income per meu

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 A2.4: Full information maximum likelihood estimates of the switching regression model – maize income per meu

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

Variables	HhldPerMzIn_1	HhldPerMzIn_0	IF2006
HHage	-9,119	13,379***	0.00610
	(12,275)	(4,363)	(0.00916)
HHedu	-627,168	351,479	0.109
	(431,999)	(237,685)	(0.429)
MaleHH	55,097	51,198	-0.0735
	(401,204)	(163,581)	(0.319)
HsizeE	-135,434**	-112,901***	0.0522
	(57,278)	(28,559)	(0.0491)
Marr	-427,665	434,810	0.957
	(1.007e+06)	(326,121)	(0.743)
Sing	-968,377	310,048	1.663**
	(1.049e+06)	(393,131)	(0.796)
Wid	-551,526	343,810	0.982
	(995,039)	(347,901)	(0.760)
HHedu2	105,581	-38,275	0.000254
	(64,737)	(37,350)	(0.0664)
SoilfertCH	218,490	11,123	0.112
	(182,452)	(94,656)	(0.169)
SandySoil	-506,195**	103,445	0.339
	(224,086)	(136,709)	(0.207)
Farmsi	196,524**	185,874***	0.309***
	(83,000)	(42,993)	(0.0669)
AreaFa	-219,824***	-154,792***	-0.0628
	(79,696)	(50,644)	(0.0869)
Chainda	-167,021	-88,966	-0.298
	(225,433)	(117,510)	(0.215)
Nyangwena	350,365	-233,749	-1.063***
	(372,586)	(149,800)	(0.272)
YrWdemand			-0.000298***
			(7.14e-05)
Constant	2.417e+06	-1.285e+06**	-2.399**
	(1.528e+06)	(545,377)	(1.052)
Rho	0.144	0.259	
	(0.573)	(0.172)	
Observations	292	292	292

Standard errors in parentheses

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

Table A2.5: Full information maximum likelihood estimates of the switching regression model – maize yield

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 A2.6: Full information maximum likelihood estimates of the switching regression model - Maize yield per ha

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

Variables	Mzydperha_1	Mzydperha_0	IF2006
HHage	-0.134	0.0717	0.159***
	(0.103)	(0.0453)	(0.0532)
HHedu	0.0768	0.146	0.101
	(0.562)	(0.394)	(0.437)
MaleHH	1.108**	0.170	0.0351
	(0.508)	(0.264)	(0.322)
HsizeE	-0.0603	-0.0459	0.0137
	(0.0684)	(0.0474)	(0.0493)
Marr	-0.932*	0.284	-0.210
	(0.491)	(0.276)	(0.319)
HHage2	0.00114	-0.000675	-0.00158***
	(0.00102)	(0.000452)	(0.000533)
HHedu2	-0.0240	-0.0115	0.00212
	(0.0843)	(0.0618)	(0.0677)
SoilfertCH	-0.183	-0.0726	0.132
	(0.233)	(0.156)	(0.171)
SandySoil	-0.00917	-0.194	0.337
	(0.276)	(0.228)	(0.208)
Farmsi	0.0463	0.120	0.323***
	(0.0823)	(0.0747)	(0.0671)
AreaFa	-0.0557	-0.0870	-0.0800
	(0.105)	(0.0837)	(0.0882)
Chainda	-0.236	-0.416**	-0.333
	(0.299)	(0.194)	(0.216)
Nyangwena	-0.498	-0.777***	-1.020***
	(0.418)	(0.260)	(0.270)
YrWdemand			-0.000244***
			(6.88e-05)
Constant	6.028**	-0.565	-4.815***
	(3.041)	(1.235)	(1.453)
Rho	0.208	0.220	
	(0.322)	(0.231)	
Observations	292	292	292

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

Table A2.7: 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

Appendix 2: OLS regression and propensity score results when the 14 farmers with intent to adopt are either included in adoption category or dropped from sample

Table A3.1: OLS regression results with 14 farmers with intention to adopt included in the adopters category

Variables[1]	Coefficient	Standard error	t statistic
IF	-626.7***	178.8	-3.51
HHage	11.78*	6.919	1.70
HHedu	32.17	76.02	0.42
Marr	-30.23	400.3	-0.08
Wid	68.56	444.0	0.15
Divor	-784.4	581.9	-1.35
MaleHH	157.4	291.0	0.54
CEU	18.16	73.05	0.25
HsizeE	13.67	85.83	0.16
TotIncome	1130	166	0.07
DistFW	-101.7	81.04	-1.25
Farmsi	70.47	54.82	1.29
AreaFa	-93.07	74.35	-1.25
Oxcarts	223.3	141.9	1.57
Chainda	-454.8**	223.4	-2.04
Katoba	842.9***	226.1	3.73
Constant	1,298**	559.1	2.32
Observations	323		
R-squared	0.198		

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
[1] for variable descriptions see Table 3.3

Table A3.2: OLS Regression results with 14 farmers with intention to adopt dropped from the sample

Variables[1]	Coefficient	Standard error	t statistic
IF2009	-838.1***	187.7	-4.46
HHage	10.72	7.090	1.51
HHedu	50.45	76.40	0.66
Marr	-161.1	396.5	-0.41
Wid	23.78	440.6	0.05
Divor	-962.7	618.9	-1.56
MaleHH	241.3	293.8	0.82
CEU	7.605	72.93	0.10
HsizeE	30.92	85.27	0.36
TotIncome	3330	168	0.20
DistFW	-75.72	81.37	-0.93
Farmsi	82.88	55.99	1.48
AreaFa	-87.67	75.35	-1.16
Oxcarts	293.7**	143.4	2.05
Chainda	-457.7**	223.5	-2.05
Katoba	817.6***	224.2	3.65
Constant	1,222**	560.8	2.18
Observations	309		
R-squared	0.216		

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
[1] for variable descriptions see Table 3.3

Table A3.3: Estimation of propensity score probit results when 14 farmers with intent to adopt are included as adopters

Variables	Coefficient	Robust standard error	Z
HHage	0.174***	0.0432	4.02
HHedu	0.292	0.340	0.86
MaleHH	0.259	0.246	1.05
Marr	0.141	0.454	0.31
Sing	0.773	0.537	1.44
Wid	0.214	0.483	0.44
logsize	0.710**	0.288	2.47
HHage2	-0.00158***	0.000416	-3.80
HHedu2	-0.0296	0.0531	-0.56
DistFW	0.115*	0.0786	1.46
CEU	-0.0919	0.0608	-1.51
Chainda	0.463**	0.187	2.48
Katoba	0.338*	0.198	1.70
Constant	-7.236***	1.234	-5.86
Observations	324		
Log pseudo likelihood	-144.23		
Wald chi2(13)	43.76		
Prob > chi2	0.0000		
Pseudo R^2	0.11		

Standard errors bootstrapped 1000 times
*** p<0.01, ** p<0.05, * p<0.1

Table A3.4: Estimation of propensity score probit results when 14 farmers with intent to adopt are dropped from the sample

Variables	Coefficient	Robust standard errors	Z
HHage	0.218***	0.0543	4.02
HHedu	0.237	0.367	0.65
MaleHH	0.395	0.261	1.51
Marr	0.607	0.580	1.05
Sing	1.433**	0.663	2.16
Wid	0.761	0.633	1.20
Logsize	0.748**	0.314	2.38
HHage2	-0.00206***	0.000539	-3.82
HHedu2	-0.0196	0.0570	-0.34
DistFW	0.173**	0.0815	2.13
CEU	-0.0927	0.0656	-1.41
Chainda	0.351*	0.195	1.80
Katoba	0.237	0.204	1.16
Constant	-8.913***	1.498	-5.95
Observations	310		
Log pseudo likelihood	-127.03		
Wald chi2(13)	46.51		
Prob > chi2	0.0000		
Pseudo R^2	0.14		

Standard errors bootstrapped 1000 times
*** p<0.01, ** p<0.05, * p<0.1

Appendix 3: ATT estimation when the 14 farmers with intent to adopt are either included in adoption category or dropped from sample

Table A3.5: ATT estimation of the causal effect of improved fallows on forest fuel wood (kg) when 14 farmers with intention to adopt included in adopters category

	Number of adopters	Number of non-adopters	Average treatment effect on the treated (ATT)	t value
Nearest neighbour matching	130	73	-319.7 (247.1)	-1.294
Kernel matching	130	171	-446.5 (188.1)	-2.373

*** p<0.01, ** p<0.05, * p<0.1
Bootstrapped standard errors in parentheses with 1000 replication samples
The numbers of treated and controls refer to actual nearest neighbour (NN) matches. Only 62 non-adopting households could be matched with the adopters

Table A3.6: ATT estimation of the causal effect of improved fallows on forest fuel wood (kg) when 14 farmers with intention to adopt are dropped from sample

	Number of adopters	Number of non-adopters	Average treatment effect on the treated (ATT)	t value
Nearest neighbour matching	116	67	-433.9 (251.2)	-1.728
Kernel matching	116	163	-550.6 (187.6)	-2.935

*** p<0.01, ** p<0.05, * p<0.1
Bootstrapped standard errors in parentheses with 1000 replication samples
The numbers of treated and controls refer to actual nearest neighbour (NN) matches. Only 63 non-adopting households could be matched with the adopters

Appendix 4: Matching balancing tests for the fuel wood consumption matching models

Table A3.7: Matching balancing tests with 14 farmers with intent to adopt part of non adopters

		Mean			% reduction	t-test	
		Treated	Control	% bias	IbiasI	t	p>t
HHage	Unmatched	47.17	46.51	5.7		0.46	0.643
	Matched	47.17	47.02	1.3	77.4	0.10	0.920
HHedu	Unmatched	3.25	2.78	42.9		3.68	0.000
	Matched	3.25	3.27	-1.4	96.8	-0.08	0.966
MaleHH	Unmatched	0.85	0.80	13.4		1.14	0.256
	Matched	0.85	0.85	2.1	84.1	0.13	0.899
Marr	Unmatched	0.84	0.81	8.6		0.73	0.465
	Matched	0.84	0.84	0.3	97.1	0.01	0.988
Sing	Unmatched	0.06	0.04	10.1		0.9	0.370
	Matched	0.06	0.05	1.7	83.3	0.09	0.931
Wid	Unmatched	0.09	0.11	-8.2		-0.69	0.488
	Matched	0.09	0.09	-0.8	89.8	-0.05	0.960
Logsize	Unmatched	1.43	1.22	43.7		3.73	0.000
	Matched	1.43	1.42	1.4	96.9	0.08	0.936
HHage2	Unmatched	2295.30	2362.90	-5.8		-0.47	0.642
	Matched	2295.30	2286.9	0.7	87.5	0.06	0.955
HHedu2	Unmatched	11.68	8.98	39.2		3.41	0.001
	Matched	11.68	11.77	-1.4	96.4	-0.08	0.938
DistFW	Unmatched	2.21	1.86	34.2		3	0.003
	Matched	2.21	2.21	0.1	99.8	0.00	0.997
CEU	Unmatched	5.36	4.80	26.1		2.25	0.025
	Matched	5.36	5.45	-4.5	82.9	-0.25	0.801
Sample		Pseudo R2	LR chi2	P>chi2	Meanbias	Medbias	
	Raw	0.157	66.33	0.000	21.6	13.4	
	Matched	0.003	0.55	1.000	1.4	1.4	

Table A3.8: Matching balancing tests with 14 farmers with intent to adopt included as adopters

		Mean			% reduction	t-test	
		Treated	Control	% bias	IbiasI	t	p> t
HHage	Unmatched	47.92	45.96	16.3		1.39	0.165
	Matched	47.92	47.37	4.6	72.0	0.34	0.734
HHedu	Unmatched	3.19	2.79	36.9		3.24	0.001
	Matched	3.19	3.20	-0.8	97.7	-0.05	0.959
MaleHH	Unmatched	0.83	0.81	4.3		0.37	0.708
	Matched	0.83	0.82	2.1	51.4	0.12	0.901
Marr	Unmatched	0.83	0.82	2.9		0.26	0.796
	Matched	0.83	0.83	1.3	55.9	0.08	0.939
Sing	Unmatched	0.05	0.04	5.9		0.53	0.598
	Matched	0.05	0.05	0.3	95.4	0.02	0.988
Wid	Unmatched	0.09	0.11	-5.3		-0.46	0.643
	Matched	0.09	0.10	-2.2	58.0	-0.14	0.893
Logsize	Unmatched	1.41	1.22	41.7		3.64	0.000
	Matched	1.41	1.40	1.6	96.1	0.10	0.920
HHage2	Unmatched	2385.50	2307.40	6.4		0.55	0.583
	Matched	2385.50	2334.1	4.2	34.3	0.31	0.756
HHedu2	Unmatched	11.33	9.02	33.5		2.98	0.003
	Matched	11.33	11.36	-0.4	98.8	-0.02	0.982
DistFW	Unmatched	2.13	1.88	24.3		2.16	0.031
	Matched	2.13	2.13	-0.1	99.5	-0.01	0.994
CEU	Unmatched	5.32	4.78	25.2		2.23	0.027
	Matched	5.32	5.38	-2.7	89.2	-0.16	0.873
Sample		Pseudo R2	LR chi2	P>chi2	Meanbias	Medbias	
	Raw	0.111	48.52	0.000	18.4	16.3	
	Matched	0.002	0.49	1.000	1.9	1.6	

Table A3.9: Matching balancing tests with 14 farmers with intent to adopt dropped from sample

		Mean Treated	Control	% bias	% reduction IbiasI	t-test t	p> t
HHage	Unmatched	47.17	45.96	10.5		0.85	0.398
	Matched	47.17	46.77	3.5	66.5	0.27	0.789
HHedu	Unmatched	3.25	2.79	42.3		3.59	0.000
	Matched	3.25	3.27	-1.8	95.8	-0.10	0.920
MaleHH	Unmatched	0.85	0.81	10.5		0.88	0.379
	Matched	0.85	0.85	2.0	81.0	0.12	0.908
Marr	Unmatched	0.84	0.82	6.7		0.57	0.569
	Matched	0.84	0.84	0.6	90.7	0.04	0.971
Sing	Unmatched	0.06	0.04	8.7		0.76	0.450
	Matched	0.06	0.06	0.7	91.5	0.04	0.970
Wid	Unmatched	0.09	0.11	-7.4		-0.62	0.533
	Matched	0.09	0.09	-1.3	81.8	-0.08	0.937
Logsize	Unmatched	1.43	1.22	44.7		3.76	0.000
	Matched	1.43	1.42	0.6	98.7	0.03	0.972
HHage2	Unmatched	2295.30	2307.40	-1.0		-0.08	0.933
	Matched	2295.30	2260.20	3.0	-191.0	0.23	0.816
HHedu2	Unmatched	11.68	9.02	38.6		3.31	0.001
	Matched	11.68	11.79	-1.6	95.9	-0.09	0.931
DistFW	Unmatched	2.21	1.88	31.5		2.71	0.007
	Matched	2.21	2.23	-2.1	93.2	-0.11	0.910
CEU	Unmatched	5.36	4.78	26.8		2.28	0.023
	Matched	5.36	5.46	-4.9	81.6	-0.27	0.785
Sample		Pseudo R2	LR chi2	P>chi2	Meanbias	Medbias	
	Raw	0.150	61.37	0.000	20.8	10.5	
	Matched	0.003	0.56	1.000	2.0	1.8	

Appendix 5: Expected annual household fuel wood consumption (kg) and full information maximum likelihood from endogenous switching regression

Table A3.10: Average expected annual household fuel wood consumption (kg) for improved fallow adopters and non-adopters with 14 farmers with intent to adopt included in adoption category

	Decision stage			
	To adopt	Not to adopt	Treatment effect	t value
Adopters (N = 130)	1825.9 (53.2)	2647.7 (71.9)	-821.8	-10.9794
Non-adopters (N = 194)	2327.5 (54.8)	2500.7 (55.6)	-173.2	-2.7328
Heterogeneity effects	BH_1 = -501.6	BH_2 = 147	TH = -648.6	

*** p<0.01, ** p<0.05, * p<0.1
The number in parentheses show standard errors
BH = the effect of base heterogeneity for households that adopted and those that did not
TH = transitional heterogeneity, the difference between the treatment effect on the treated or adopters (TT) and the treatment effect on the untreated or non-adopters (TU)

Table A3.11: Average expected annual household fuel wood consumption (kg) for improved fallow adopters and non-adopters with 14 farmers with intent to adopt dropped from sample

	Decision stage			
	To adopt	Not to adopt	Treatment effect	t value
Adopters (N = 116)	1742.8 (62.6)	2803.1 (77.3)	-1060.3	-11.8338
Non-adopters (N = 208)	2327.7 (54.8)	2714.6 (80.3)	-386.9	-4.4902
Heterogeneity effects	BH_1 = -584.9	BH_2 = 88.5	TH = -673.1	

*** p<0.01, ** p<0.05, * p<0.1
The number in parentheses show standard errors
BH = the effect of base heterogeneity for households that adopted and those that did not
TH = transitional heterogeneity, the difference between the treatment effect on the treated or adopters (TT) and the treatment effect on the untreated or non-adopters (TU)

Table A3.12: Full information maximum likelihood estimates of the endogenous switching regression model – 14 farmers with intent to adopt relegated to non-adoption category

Variables	Fuel wood demand_1	Fuel wood demand_0	IF2009
HHage	-209.5**	91.98*	0.224***
	(84.85)	(51.31)	(0.0496)
HHedu	164.9	-566.3	0.291
	(482.7)	(445.7)	(0.386)
MaleHH	-103.2	283.7	0.257
	(436.3)	(344.7)	(0.316)
Marr	1,576	971.8*	0.829
	(1,078)	(566.6)	(0.688)
Sing	2,146*	1,037	1.758**
	(1,118)	(740.9)	(0.753)
Wid	1,115	1,355**	0.996
	(1,054)	(598.0)	(0.708)
logsize	-12.22	171.9	0.554*
	(402.4)	(375.4)	(0.318)
HHage2	2.650***	-0.907*	-0.00216***
	(0.833)	(0.503)	(0.000485)
HHedu2	-6.992	87.78	-0.0230
	(71.20)	(72.53)	(0.0596)
DistFW	-107.4	-17.71	0.229***
	(101.9)	(115.8)	(0.0848)
CEU	30.09	28.37	-0.0883
	(76.37)	(83.92)	(0.0687)
AreaFa	-69.14	113.5	0.242***
	(68.20)	(83.77)	(0.0625)
Chainda	57.27	-811.4***	0.603**
	(315.9)	(279.1)	(0.246)
Katoba	738.8**	988.6***	0.614**
	(316.2)	(297.7)	(0.254)
SandySoil			0.636***
			(0.201)
Totfertuse			0.0111
			(0.161)
Constant	3,663	-551.8	-9.241***
	(2,963)	(1,562)	(1.571)
Rho	-0.145	0.317	
	(0.284)	(0.212)	
Observations	324	324	324

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
CEU = Consumer equivalent units (CEU) were calculated following Runge-Metzger (1988) as: < 9years = 0.4; 9 to 15 = 0.7; Males 16 to 49 = 1; Females16 to 49 = 0.9 and over 49 years = 0.8

Table A3.13: Full information maximum likelihood estimates of the endogenous switching regression model – 14 farmers with intent to adopt relegated to adoption category

Variables	Fuel wood demand_1	Fuel wood demand_0	IF
HHage	-77.69	65.55	0.174***
	(88.21)	(52.91)	(0.0437)
HHedu	-60.63	-348.2	0.339
	(522.6)	(472.1)	(0.365)
MaleHH	-352.0	314.1	0.0946
	(454.9)	(355.8)	(0.295)
Marr	1,493*	710.6	0.124
	(786.5)	(636.6)	(0.537)
Sing	1,737**	845.1	0.766
	(859.2)	(775.3)	(0.614)
Wid	641.7	1,166*	0.140
	(753.8)	(673.1)	(0.558)
logsize	-182.1	223.2	0.565*
	(455.3)	(389.3)	(0.305)
HHage2	1.188	-0.635	-0.00160***
	(0.836)	(0.516)	(0.000420)
HHedu2	24.61	54.29	-0.0340
	(77.68)	(76.62)	(0.0568)
DistFW	-93.66	-21.98	0.137*
	(106.7)	(117.4)	(0.0816)
CEU	47.35	26.83	-0.0953
	(84.48)	(86.77)	(0.0653)
AreaFa	-86.89	130.4	0.226***
	(79.89)	(88.10)	(0.0597)
Chainda	-116.4	-778.2**	0.778***
	(377.0)	(311.1)	(0.233)
Katoba	629.1*	975.3***	0.741***
	(369.4)	(322.1)	(0.242)
SandySoil			0.514***
			(0.199)
Totfertuse			-0.0132
			(0.158)
Constant	1,704	-124.3	-7.051***
	(3,212)	(1,590)	(1.356)
Rho	0.001	0.317	
	(0.380)	(0.240)	
Observations	324	324	324

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
CEU = Consumer equivalent units (CEU) were calculated following Runge-Metzger (1988) as: < 9years = 0.4; 9 to 15 = 0.7; Males 16 to 49 = 1; Females16 to 49 = 0.9 and over 49 years = 0.8

Table A3.14: Full information maximum likelihood estimates of the endogenous switching regression model – 14 farmers with intent to adopt dropped from sample

Variables	YrWdemand_1	YrWdemand_0	IF2009
HHage	-211.4**	67.77	0.222***
	(84.41)	(53.56)	(0.0501)
HHedu	162.8	-381.3	0.272
	(482.3)	(468.6)	(0.391)
MaleHH	-103.7	328.6	0.229
	(436.2)	(355.7)	(0.319)
Marr	1,589	776.9	0.674
	(1,076)	(640.4)	(0.749)
Sing	2,155*	932.6	1.547*
	(1,110)	(788.6)	(0.811)
Wid	1,132	1,241*	0.776
	(1,051)	(677.8)	(0.780)
Logsize	-17.39	198.5	0.569*
	(402.7)	(384.2)	(0.319)
HHage2	2.665***	-0.665	-0.00211***
	(0.826)	(0.526)	(0.000490)
HHedu2	-6.708	59.44	-0.0217
	(71.19)	(76.25)	(0.0605)
DistFW	-107.3	-11.86	0.208**
	(100.1)	(118.8)	(0.0858)
CEU	30.55	32.63	-0.0911
	(76.43)	(85.84)	(0.0690)
AreaFa	-70.56	127.3	0.241***
	(67.99)	(86.71)	(0.0629)
Chainda	45.31	-818.1***	0.682***
	(320.1)	(298.0)	(0.249)
Katoba	730.4**	945.9***	0.664***
	(318.3)	(310.1)	(0.255)
SandySoil			0.615***
			(0.203)
Totfertuse			0.00442
			(0.162)
Constant	3,731	-214.1	-8.982***
	(2,924)	(1,619)	(1.601)
Rho	-0.160	0.304	
	(0.282)	(0.229)	
Observations	310	310	310

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
CEU = Consumer equivalent units (CEU) were calculated following Runge-Metzger (1988) as: < 9years = 0.4; 9 to 15 = 0.7; Males 16 to 49 = 1; Females16 to 49 = 0.9 and over 49 years = 0.8

Appendix 6: Household survey questionnaire

Farmer welfare and environmental impact of improved fallows survey

Name of Enumerator ……………………………….

Date of Interview……………………………………

Supervisor (Kuntashula)

Section A: Household Identification Details	Coding
1. What is your status in the household?	*1=head of household, 2= spouse, 3=child, 4= worker,5= mother,5= father, 6=other relative*
2. Name of Household Head/Respondent	
3. Sex of household head	*1= Female 2=Male*
4. District	
5. Agricultural Block	
6. Camp	
7. Village	

Section B: Basic Household Information	Coding
8. Educational Level of Head of HH	*1. Never been to School* *2. Primary* *3. Secondary* *4. Tertiary*
9. Age of the head of Household (years)	………………. Years
10. Marital Status of Household head	*1. Married* *2. Widow* *3. Widower* *4. Bachelor* *5. Spinster* *6. Divorced*

Household Composition								
	Under 5		**Children (6-17)**		**Adults (18-59)**		**Elderly (60+)**	
	M	**F**	**M**	**F**	**M**	**F**	**M**	**F**
11. No. of people living in homestead:								
12. No. of chronically ill								

"living" is defined as someone who stays there at least for three months in a year)
chronically ill is defined as, *sick and unable to work for a total of 3 months over the last 12 months*

12. When did the household start using improved fallows (IFs)? ___________________________

13. Is the information given so far the same as it was when the households started using IFs (or 6 yrs ago for non-users)? If there is a change, what has change? _________________________
____

Does household posses any of the following physical assets? (tick all that apply)	**Quantity Owned (Now)**	**Quantity Owned year they started using IF (or 6 years ago for non-users)**
14. ☐Cattle		
15. ☐Goats		
16. ☐Poultry		
17. ☐Pigs		
18. ☐Donkeys		
19. ☐Ox carts		
20. ☐Ox drawn ploughs		
21. ☐Ox drawn harrows		
22. ☐Cultivators		
23. ☐Ridging plough		
24. ☐Knapsack sprayers		
25. ☐Bicycles		
26. ☐Radios		
27. ☐TV set		

28. Does the household or any member of the household belong to any farming related group?

1= Yes *2= No* (if No. jump next two Qns)

29. If Yes, What is the main purpose of the organization? _______________________
____

30. When did the household join the organization cited above? _______________

Does household receive income from the following livelihood strategies? (tick all that apply)	**Approximate how much per year (ZK)** – use the last 12 months period
31. ☐ Petty trading (Specify)	
32. ☐ Gardening activities/Off season farming	
33. ☐ Local chicken rearing	
34. ☐ Goat rearing	
35. ☐ Cattle rearing	
36. ☐ Remittances	
37. ☐ Sale of rain fed food crops (specify)	
38. ☐ Sale of rain fed cash crops (specify)	
39. ☐ Piece work	
40. ☐ Sale of charcoal	
41. ☐ Other (Specify)	

Section C: Agricultural Practices

42. What are the major agricultural related challenges that the household faces *(list them in order of severity, with most severe ranked as 1)*: ____
____

43. Are these the same challenges the household faced when they first started using IFs (or 6 yrs ago for non-users)? If not, what has changed? ____
____

44. How much land do you own? _______________(*owned = exclusive long-term access*)

45. How much land is usually uncultivated on your farm? _________________________

46. Fill in the below Table for the various main cropping fields for last season

Field	Crop planted	Total area planted	Applied *(1= fertilizer 2= manure 3=used improved fallows 4=no nutrients)*	Name of manure or fertilizer or specie of improved fallow	Quantity of manure or fertilizer applied	Total crop production (*include units*)
1	Maize					
2	Sorghum					
3	Groundnuts					
4	Cotton					
5	Sunflower					
6	Other (specify)					

47. Have the farming practices mentioned in the above Table remained the same since you started using IFs (or in the last 6 years)? *1=Yes 2=No*

48. If No, what has changed (be specific) ____

52. At how much did you sell the crops harvested from your fields?

Maize: ______________________________
Sorghum: ___________________________
Groundnuts: _________________________
Cotton: _____________________________
Sunflower: __________________________
Other (specify): ______________________

49. Please indicate if the following tree crops are growing on your land

Trees	**1=Yes, 2=No**	**Area**
Sesbania sesban		
Gliricidia sepium		
Cajanus cajan		
Tephrosia		
Faidherbia albida (musangu tree)		
Other tree (specify)		

50. Which field had improved fallows before planting your crop? *Field 1, 2, 3, 4, 5* (confirm with Qn 46 on the number of field)

51. What was the specie of the improved fallow trees?
1=Sesbania sesban 2= Gliricidia sepium 3=Cajanus cajan 4=Tephrosia vogelii 5= Faidheibia albida

52. How much was the yield of the crop 1) year after cutting trees__________________ 2) Second year after cutting trees____________________ 3) Third year after cutting trees______________________________

53. In your own views, what are the major advantages of improved fallows compared to other soil replenishment remedies such as inorganic fertilisers?_____________________________
____
____

54. In your own views, what are the major disadvantages of improved fallows compared to other soil fertility replenishment remedies such as inorganic fertilisers?____________________
____
____

55. How many months per year do you have enough own grown food for all members of the household? ___________

56. Which months don't you have enough own grown food? __________________________

57. What do you do to ensure you have enough food during these months? ______________
____

58. How many months per year did you have enough own grown food for all members of the household before embracing IFs (or 6 yrs ago for non-adopters)? ___________

59. May you list the environmental impacts of improved fallows in order of importance
____
____

60. Do you experience soil erosion on your farm?

61. How severely degraded is the plot that has/had improved fallows?

1=Very eroded 2= Eroded 3=Barely Eroded

62. How severely degraded is the plot that had used inorganic fertilisers?

1=Very eroded 2= Eroded 3=Barely Eroded

63. How severely degraded is the plot that has/had used kraal manure?

1=Very eroded 2= Eroded 3=Barely Eroded

64. How severely degraded is the plot that did not use any external inputs?

1=Very eroded 2= Eroded 3=Barely Eroded

Section D: By-products from Improved Fallows and the Natural Forests

65. How many times per month do you collect fire wood from the forest? ____________

66. Approximate the average weight of fire wood collected every time the household collect ____________________________ kgs (*weigh what is available and ask farmer how much more is required to reach monthly quantity*)

67. Have you ever used the trees from improved fallows as fire wood? 1 = Yes 2 = No

68. If yes to Qn 52, how many months or days did the fire wood from the fallows last? _________

69. How many times per year do you collect small structure construction materials? ____

70. Have you ever used materials from improved fallows for construction of farm structures? *1 = Yes 2 = No*

71. If yes, which structure did you construct? ____________________when____?

72. For the farmers who have used improved fallows before, *fill in the following Table for the various products of improved fallows at fallow termination.*

Product	Tree species	Quantity obtained from IFs (include units)	If sold, how much (ZK)	If not sold, estimated value of product (ZK)
Fire wood				
Hoe handles				
Poles for building structures				
Roofing wood				
Mbalo				
Charcoal				
Livestock fodder				
Fencing wood				
Medicine for livestock				
Chemicals for crop or grain				
Other (specify)				
Other (specify)				

73. For all farmers, estimate the s*ources of various products listed in the below Table for the past 12 months*

Product	Total used in 12 months (specify units)	Amount sold if any	Estimated proportion (%) from			
			Improved Fallows	Natural Forests	bought or bartered	Relatives or friends- received free
Fire wood						
Hoe handles						
Poles for building hut						
Poles for building latrine						
Roofing poles						
Charcoal						
Mbalo						
Livestock fodder						
Hoe & axe handles						
Medicine for livestock						
Chemicals for crop or grain						
Thatching grass						
Livestock fodder						

If units are in bundles (fire wood, poles etc), or bags (charcoal etc) estimate with farmer approximate units in kgs.

THE END –Thank you for your time!