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Are sustainable agricultural practices improving output and incomes of smallholder farmers in Malawi?

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Abstract- *Sustainable agricultural practices could promote agricultural development. They have proven to improve soil structure, moisture content and reduce competition from weeds. There are, however, mixed reactions to the impacts of these technologies. Opponents argue that some technologies are labor intensive, bind nutrients in the soil and decrease crop yields in the short run. This study examines impacts of sustainable intensification strategies on maize output and household full income using random survey data from Malawi. The study employs multinomial endogenous switching regressions on a typology of farm households to isolate direct causal effects of these technologies. It triangulates the results with reduced form propensity score matching. Average Treatment Effects on the Treated are reported. Results indicate that socioeconomic, geographical and plot characteristics influence adoption decisions. Further, farmers who adopt sustainable agricultural practices such as improved seed and soil and water conservation have consistently more farm output and incomes than non-adopting households.*

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1. Introduction

As population of Sub-Saharan African (SSA) countries increases, some key questions that still remain to be answered are how people will be fed and how they will be taken out of poverty. Most countries in SSA are land locked resource poor and rely on rain fed agriculture to achieve their food security requirements. One reason for dominance of agriculture is that capital output ratios in these countries are low and the primary source of employment is farming which employs a larger proportion of the population. As population grows and climate changes, sustainable solutions to food and poverty problems lie within the agricultural sector itself. However, in most SSA countries agriculture is practiced by resource constrained small holder farmers, who ply their trade in failed institutions, weak infrastructural settings and general market failure. As such, most farming practices are destructive to the environment and result in low yields. With weather variability as an effect of climate change, low yields resulting from poor farming practices challenge food security (New Partnership for Africa's Development (NEPAD), 2003).

Amidst myriad innovations and technologies, sustainable agricultural practices (SAPs) are considered a panacea to most problems smallholder farmers face when they engage in farming activities (Sambo et al., 2011; Kirkegaard et al. 2012). SAPs comprise a highly advocated bundle of technologies for conserving soil and water because they reduce run-off, improve moisture content and reduce soil temperature (Giller et al. 2009). It has further been argued that in the long run, intensification technologies reduce soil erosion, increase soil organic matter, improve soil aggregation and nitrogen mineralization. Advocates for intensification argue that increased yields from intensifying farms may lead to increased national production which could have large output multipliers with other sectors of the economy and may reduce environmental degradation (SciDev.Net, 2015). For instance, large traded surpluses realized by households could lead to increases in household incomes in rural areas (Sosola et al., 2011). However, some studies have also argued that under some intensification methods such as Conservation Agriculture (CA) lead to poor seed germination, increased weed competition, high incidence if pests and diseases and in some cases water logging (Giller et al., 2009).

Conventional agriculture is frequently questioned on whether it can adequately address food security issues while at the same time ensuring sustainable use of resources. Proponents argue that sustainability can be achieved through intensification since one of the pillars of the technology bundle is soil and water conservation achieved through zero tillage. For instance in a study conducted in Balaka district of Malawi, Ngwira et al., (2012) indicated that intensification strategies such as CA result in major resource savings as labor costs are significantly lower than conventional agriculture. Munthali et al. (2009) also found that CA yields were higher than in conventional agriculture.

Intensification strategies could result in better yields if mixed with other technologies and consistently practiced over time. Giller et al. (2009) observed that in the short-term, if herbicides are not used, intensification practices such as CA could result in an increase in labor costs. Ngwira et al., (2012) also presents a case that CA increases pests such as earthworms but their populations are reduced in the case where maize is intercropped with legumes. Furthermore, Kirkegaard et al. (2012) adds that yield effects are modest if CA is not mixed with other innovations. Chikowo et al. (2004) indicated that in the first two seasons that SAPs are being implemented, farmers might appear to be losing out relative to others who are under conventional agriculture but Thierfelder et al. (2013) reported that yield benefits of CA could be observed in the fifth season after CA but could also be observed immediately.

Institutional and cultural constraints act as barriers to adoption of SAPs. Ngwira et al. (2014) noted that adoption of intensification strategies such as CA in Malawi presents a unique set of constraints and extension policy should aim at reducing information barriers and provide direct support to farmers to increase adoption. Among others, Ngwira et al. (2009) and Williams (2008) pointed out that CA has not been fully embraced since there are cultural constraints that need to be overcome.

Literature on effects of intensification on different circumstances facing smallholders seems to be mixed and utmost contradictory due to lack of in-depth analysis of available data. Literary evidence suggests that some practices could not benefit smallholder farmers (Giller, 2009) while others like (Ngwira et al., 2012; Kakhobwe et al. (2012)) suggest that they could increase profitability, income and food availability at household level. Most of the studies cited have been experimental (Chikowo, et al. 2004) and descriptive (Ngwira et al. 2012) and lack farmer characteristics and circumstances. Such omitted variables are key in the analysis and could alter outcomes. Thus information in the available literature is missing on whether farmers adopting sustainable agricultural practices actually achieve higher outputs and tradable surpluses which eventually lead to increased incomes when all necessary factors have been carefully accounted for.

This paper uses multinomial endogenous treatment regressions (MESR) and propensity score matching (PSM) techniques in order to establish direct causal links between sustainable agricultural practices, household farm output and income. A multinomial endogenous switching regression model is a framework that isolates treatment effects in a multinomial setting on a continuous non-negative outcome variable (Deb & Trivedi, 2006) in this case maize output and farm income. Propensity score matching is a non-experimental, semi-parametric, statistical evaluation strategy that estimates the effect on an intervention by controlling for observable factors that affect the intervention. The method reduces bias due to confounding factors by estimating the effect of the intervention on individuals that have similar characteristics with the treated group rather than just comparing treated and untreated groups (Khandker et al. 2010). The major contribution of the paper to SAPs and technology adoption literature is that it presents direct causal effects which vary by location and farmer typologies using cutting edge econometric techniques.

The rest of the paper is structured as follows; section two presents the analytical technique. It details the impact evaluation problem and presents the propensity score matching framework. Section three presents data sources and descriptive statistics. Section four presents results and discussion and section five presents conclusion and policy implications.

2. Analytical technique

2.1. Evaluation of causal effects of sustainable agricultural practices

Household incomes and food security at household level may increase by several factors. Resultant, attributing a change in income or food security to one cause, in this case, SAPs may be a complex process that requires careful attention. Several, studies on SAPs were conducted in experimental settings and there is little doubt that their findings could really portray causal effects. However, when it comes to dealing with people, it becomes challenging to observe how the same individual could have performed had it been that they did not adopt the intervention in question. Thus it presents a classic case of missing data (Mendola, 2007). In order, establish direct causal effects of SAPs on household incomes amidst a number of factors that can potentially affect it, a number of statistical considerations need to be taken.

First, households, seeing the potential benefits or disadvantages thereof, decide whether to engage in sustainable agricultural practices or not. This is called “self-selection”. There is a bi-directional line of causality between practicing SAPs and increasing incomes and food security. That is, households may adopt technologies in order to increase their incomes and households with high incomes may adopt technologies because they have the monetary resources to do so. In view of this, establishing direct causal effects by just comparing SAPs adopting households and conventional agriculture practicing households may lead to erroneous conclusions. Thus, identification of the individuals may be random, but the adoption decision may not be random. Therefore, statistical techniques need to be employed in order to isolate policy relevant causal effects of intensification.

2.2. *Model and estimation strategy*

In an experimental setting, a simpler way of isolating direct causal effects is to simply take the difference in average incomes of households that adopted SAPs and households that practiced conventional agriculture. However, in a real world setting it would require a systematic statistical approach to the analysis of direct causal effects (Khandker, et al. 2010).

Farmers in Malawi adopt SAPs in a number of ways i.e. they can adopt the entire package, or adopt bits of the technology (Thierfielder et al. 2013). In evaluating choice of farming practice, utility of the technologies matters. We, therefore, assume that farmers adopt m sustainable agricultural practices in order to maximize utility, U_i. In order for farmer i to adopt practice j over other practices, m, the expected change in utility from adopting practice *j* must exceed the change in utility from adopting the other *m* practices, that is, $U_{ij} > U_{im}$ for all $m \neq j$. Thus, a household adopts SAPs if the marginal utility of adoption a practice is greater than that of practicing conventional farming. That is $\Delta U_{im} = U_{ij} - U_{im} > 0$ for all $m \neq j$. Further, the expected utility, U_{ij}^{*}, from adopting an alternative j is a latent (hidden) variable which can be explained by household, farm and geographical observable characteristics (X_i) and unobservable characteristics (ϵ_{ij}). Mathematically the expected utility can be presented as

Equation 1- $U_{ij} = X_i\beta_j + \epsilon_{ij}$

where B_j is a vector of unknown parameters to be estimated. If we construct an index *I* which denotes the farmers' choice of a practice, in a way that

Equation 2- $$I = \begin{cases} 1 \text{ if } \mathrm{U}^*_{\mathrm{ij}} > \max(U^*_{im}) \text{ or } \eta_{\mathrm{i1}} < 0 \\ \vdots \qquad\qquad \vdots \qquad\qquad \forall \text{ m} \neq \text{j} \\ J \text{ iff } U^*_{ij} > \max(U^*_{im}) \text{ or } \eta_{ij} < 0 \end{cases}$$

where $\eta_{ij} = \max\limits_{m \neq j}\left(U^*_{im} - U^*_{ij}\right) < 0$. The second equation that the *i*th farmer will adopt practice *j* if this provides expected utility that is greater than the other strategies. That is if $\eta_{ij} = \max\limits_{m \neq j}\left(U^*_{ij} - U^*_{im}\right) > 0$ (Teklewold, 2013).

This framework assumes that the error terms ϵ are identically and independently Gumbel distributed. In this case, the probability that a given farmer *i* adopts a particular SAP *j* can be estimated using a multinomial logistic regression model following McFadden (1973). The model can be mathematically presented as

Equation 3- $$P_{ij} = \Pr(\eta_{ij} < 0|X_i) = \frac{\exp(X_i\beta_j)}{\sum_{m=1}^{J} \exp(X_i\beta_m)}$$

where the parameters are as defined and can be estimated through a maximum likelihood procedure as log of odds against a particular base category.

After the multinomial logistic regression model we proceed and fit an endogenous switching regression model. In this model we use the exogenous variables *Z*, such as household characteristics, plot characteristics to explain the outcome variables such as income and farm output. In the sustainable intensification package, the base category is the non-adopters who used local varieties, and did not use any soil and water conservation practices. Since almost everyone (>75 percent) used fertilizers, we did not consider fertilizer as an exclusion criterion. Thus the base category will be denoted as $j = 1$. From then on, we get a number of regimes which are all functions of the exogenous variables as:

Equation 4- $$\begin{cases} \text{Regime 1: } Q_{i1} = Z_i\alpha_1 + u_{i1} \quad \text{if} \quad I = 1 \\ \vdots \qquad\qquad \vdots \qquad\qquad \vdots \qquad\qquad \vdots \\ \text{Regime J: } Q_{i1} = Z_i\alpha_1 + u_{i1} \quad \text{if} \quad I = J \end{cases}$$

We denote $Q'_{ij}s$ as outcome variables the *i*th farmer faces after adopting regime *j*. We assume that error terms $(u's)$ are distributed with $E\left(u_{ij}\middle|X, Z\right) = 0$ and $\mathrm{var}\left(\mathrm{u_{ij}}\middle|X, Z\right) = \sigma_j^2$. Noteworthy, the outcome, Q_{ij}, is observed only when practice j is adopted. Thus its expected utility is greater than m, that is, $U_{ij}^* > \max_{j \neq m}(U_{ij}^*)$. If the error terms, ϵ's and u's are not independent, then one cannot estimate the outcomes using Ordinary Least Squares (OLS) regression methods because they will result in biased estimates. In that case, to estimate the parameters, α_j, consistently, it is important to account for the selection process. That is, we should account for the selection of the other alternatives within the intensification package. Thus we invoke the following linear assumption about the relationship between the error terms, ϵ's and u's

Equation 5- $$E(u_{ij}|\epsilon_{i1} \ldots \epsilon_{ij}) = \sigma_j \sum_{m \neq j}^{J} r_j(\epsilon_{im} - E(\epsilon_{im})).$$

Further, the linear combination of the correlations between the errors is equal to zero i.e. $\sum_m^J r_j = 0$. We then use this assumption to specify the multinomial endogenous switching regression model as

Equation 6- $$\begin{cases} \text{Regime 1: } Q_{i1} = Z_i\alpha_1 + \sigma_1\hat{\lambda}_1 + \omega_{i1} & \text{if } I = 1 \\ \vdots \quad \vdots \quad \vdots & \vdots \\ \text{Regime J: } Q_{i1} = Z_i\alpha_1 + \sigma_J\hat{\lambda}_J + \omega_{i1} & \text{if } I = J \end{cases}$$

In Equation 6, σ_j shows how much u's and ϵ's change together, i.e. covariance while the λj is a ratio of the probability density function to the cumulative distribution function of the selection variable i.e. the Inverse Mills Ratio (IMR). The IMR is computed using the probabilities predicted from Equation 3 in the following way:

Equation 7- $$\lambda_j = \sum_m^J \rho_j \left[\frac{\hat{P}_{im}\ln(\hat{P}_{im})}{1-\hat{P}_{im}} + \ln(\hat{P}_{ij})\right].$$

In equation 7 the ρ is a measure of the correlations between ϵ's and u's. The ω's are respectively error terms with an expected value equal to zero i.e. $E(\omega_{ij}) = 0$. Considering that the agricultural intensification package in question.

2.3. *Estimation of average treatment effects*

Using the theoretical framework above, we evaluate Average Treatment Effects on the Treated (ATT) by comparing expected outcome variables of SAP adopters and those of non-adopters. We present counterfactual scenarios in the following manner:

SAP adoting households as are observed in the sample i.e. adopters:

Equation 8- $$\begin{cases} \mathrm{E}(Q_{i2}|I=2) = Z_i\alpha_2 + \sigma_2\hat{\lambda}_2 \\ \quad\vdots \qquad\qquad \vdots \qquad\qquad \vdots \\ \mathrm{E}(Q_{i2}|I=J) = Z_i\alpha_J + \sigma_J\hat{\lambda}_J \end{cases}$$

SAP adopting households had they chosen not to adopt (Counterfactual)

Equation 9- $$\begin{cases} \mathrm{E}(Q_{i1}|I=2) = Z_i\alpha_1 + \sigma_1\hat{\lambda}_2 \\ \quad\vdots \qquad\qquad \vdots \qquad\qquad \vdots \\ \mathrm{E}(Q_{i1}|I=J) = Z_i\alpha_J + \sigma_J\hat{\lambda}_J \end{cases}$$

We use expected values of the outcomes to obtain estimates of ATT. The ATT is defined as

Equation 10- $$ATT = E[Q_{i2}|I=2] - E[Q_{i1}|I=2] = Z_i(\alpha_2 - \alpha_1) + \lambda_2(\sigma_2 - \sigma_1)$$

The right hand-side of equation 10 shows the expectation of the change in the adopters when adopters have the same characteristics with non-adopters. The λ_i is the term that accounts for selection by capturing all the possible effects of unobservable random variables.

2.4. Propensity score matching

Propensity score matching can be used to evaluate direct causal effects of programs in a multinomial setting in two stages. First, consider potential income Y_{im}^{T} for the i^{th} household that practices the m^{th} SAP component. Then household income can be presented using a reduced form model as:

Equation 11- $$Y_{im}^{T} = F^{T}(X_{im}) + \varepsilon_{im}^{T} \qquad T = 0,1,\ldots,M$$

where potential incomes that will be realized from adopting the practices are $\{Y_{im}^{0}, Y_{im}^{1}, \ldots, Y_{im}^{M}\}$. The rest of the outcomes are considered counterfactuals. Further, there are a number of factors that explain household income which are contained in function $F^{T}(X_{im})$. Thus, X_{im} denotes a vector of the observed factors. Nevertheless, not all factors influencing household incomes are observable. In that case, ε_i^{T} represents all the unobservable factors (Khandker et al. 2010).

Mendola (2007) reported that household adoption of technology makes production and consumption decisions almost inseparable. Thus, the same factors that affect technology adoption also affect incomes and consumption. Therefore, to ascertain whether households adopt SAPs in order to gain incomes or they adopt SAPs because they have incomes is the major focus of this study. The study will analyze the correlation that exists between adoption and income. If will further analyze the underlying causation in the relationship. The Average Treatment Effect (ATE) denoted as:

Equation 12- $\alpha = E(Y_{im}^{1} - Y_{im}^{0})$

is the variable that enables direct causal analysis. It is the multiple treatment version of the ATE. However, the problem in observational studies is that we can only observe Y_{im}^{1} and not Y_{im}^{0}. So the observation of the income variable is a weighted average of the treated and the untreated denoted as:

Equation 13- $Y_i^T = T_{im} \cdot Y_{im}^{1} + (1 - T_{im}) \cdot Y_{im}^{0}$

Thus, the ATE would be expanded as:

Equation 14- $\alpha = P \cdot [E(Y^1|T = 1) - E(Y^0|T = 1)] + (1 - P) \cdot [E(Y^1|T = 0) - E(Y^0|T = 0)]$

The probability of adopting a SAP component, $T = 1$, is presented by P. Thus, the ATE presents a weighted average of adopters and non-adopters of SAPs in various components. The first item on the left hand side represents adopters while the last item non adopters. In as much as Eq.5 estimates the ATE, it fails to capture unobservable situations when $E(Y^1|T = 0)$ and $E(Y^0|T = 1)$. If the SAPs were randomly assigned, the counterfactual $E(Y^1|T = 0)$ would have been replaced by the actual income $E(Y^1|T = 1)$ since the would approximately be equal (Mendola, 2007). Nevertheless, the ATE just compares treated and control groups based on observable characteristics but what is of much interest is to present a case that shows the difference in income from adopting SAPs as compared to merely practicing conventional agriculture for a household i which is randomly selected from the adopters sample. This parameter is called the Average Treatment Effect on the Treated (ATT). It is the closest comparison group to the counterfactual (Ravallion, 2001). That is, Equation 15- $ATT = E[Y_{im}^1 - Y_{im}^0 | T_{im} = 1]$

It estimates the average return for adopters, conditioning on the adopters adopting. When there is self-selection, ATE and ATT will not be the same since there will be a bias due to the counterfactual situation, $E(Y^1|T = 0) - E(Y^0|T = 1)$.

Mendola (2007) argues that the household income equation, Eq. 11, cannot be estimated using ordinary least squares regression because it yields biased estimates of the impact due to self-selection. Therefore, to estimate causal effects we make a number of assumptions for the outcome. First, we assume that given some factors X_{im} that are not affected by treatment i.e. SAPs adoption status, the potential outcomes, Y_{im}^T are independent of the way adoption of SAPs, T_{im}, which is the treatment, was assigned. This is called the Conditional Independence Assumption (CIA) or the confoundedness assumption (Rosenbaum & Rubin, 1983). Lechner (2001) argues that the reduced form approach does not violate CIA. Hence, given Y_{im}^1 and Y_{im}^0, the conditional independence assumption infers

Equation 16 – $(Y_{im}^1, Y_{im}^0) \perp T_{im} | X_{im}$

The confoundedness assumption implies that the effect of SAPs on incomes is solely based on observable characteristics (Khandker et al. 2001). Estimation of ATT assumes that

Equation18 – $Y_{im}^0 \perp T_{im} | X_{im}$,

which is a weaker assumption compared with the ATE one. In practice, however, the confoundedness assumption is difficult to achieve and only the weaker ATT assumption is used.

The second assumption we make is called the common support assumption. The assumption $0 < P(T_{im} = 1 | X_{im}) < 1$, guarantees that treatment observations have comparison observations "nearby" in the propensity score distribution. The assumption requires that there should be a large number of treated and controls so that a large region of common support should be identified. In the ATT case, the assumption is reduced to $P(T_{im} = 1 | X_{im}) < 1$. All the treatment and comparison groups will then have similar characteristics. All observations with different characteristics will be dropped due to incomparability (Khandker, et al. 2010; Mendola, 2007).

The first step in propensity score matching is estimating a model for participation. We pool observations from adopters and non-adopters of CA components. After considering observed factors that are most likely going to determine participation, we fit a probit model which predicts the probability of adopting CA $P(T_{im} = 1|X_{im})$. After the probit model, the predicted values T are predicted. Hence, the predicted values are the predicted probabilities of participating $\hat{P}(T_{im} = 1|X_{im}) = \hat{P}(X)$ i.e. propensities. Nevertheless the equation for participation is not necessarily a determinants model but just a stage for estimating the propensities. Therefore, we do not interpret the t-statistics and the R-squared as they could be misleading (Khandker et al. 2010).

The second step is to determine the region of common support and conduct balancing tests. The region of common support is defined where the distribution of the propensity score for the participants and non-participants overlap. Observations outside the overlap are dropped. We also check balancing tests by observing that the in each quantile of propensity scores, the mean for participants and non-participants is the same for all observed X. If that is achieved we can be assured that $\hat{P}(T_{im} = 1|X_{im}) = \hat{P}(T_{im} = 0|X_{im})$ (Khandker et al. 2010; Ravallion, 2001).

The third step is assigning participants and nonparticipant based on their propensity score. We use Nearest-neighbor matching technique where each participant is matched with a control with the nearest propensity score. Five nearest neighbors are used in this study (Khandker et al. 2010; Ravallion, 2001).

3. Data and descriptive statistics

3.1. Data sources and descriptive statistics

We use data from the 2014 Adoption Pathways Project. This is a recent most comprehensive, randomly sampled, technology adoption data set that captures different innovations. The Adoption pathways project aims at understanding smallholder farmers' decision making processes about their farming practices and adoption of technology. The project views farmer decision making in their socioeconomic and farming systems context. The project builds on the Sustainable Intensification of Maize based Legume Systems (SIMLESA) program in order to enhance evidence based decision making regarding incentives and barriers to adoption among smallholder farmers in Malawi. The project is funded by the Australian Centre for International Agricultural

Research (ACIAR) and is implemented in the East and Southern African Region by the International Maize and Wheat Improvement Centre (CIMMYT). The Malawi component of the project is implemented by the Lilongwe University of Agriculture and Natural resources (LUANAR).

Semi-structured questionnaires were administered to respondents. The same questionnaire was used for adopters and non-adopters to ensure that the region of common support should be larger and to carter for systematic differences in the sampled households. In order, to triangulate the results, focused group discussions and key informant interviews were used. Probability proportionate to size (PPS) sampling procedure was used to arrive at a sample size of 732 households. PPS sampling procedure is ideal because it ensures that the data collected is self-weighting and increases representativeness.

Table 1 summarizes combinations of sustainable intensification strategies that are practiced by farming households in the sample. The last column of the table indicates proportions that each of the combinations presents. In general, three out of the eight possible combinations had frequencies above 10 percent of the data. Some categories such as $S_0M_1L_0$, $S_1M_1L_0$ and $S_0M_0L_0$ had observations above 10 percent of the entire sample. The category of households that grew local maize but did not practice soil and water conservation and also did not intercrop were defined as non-adopters of SAPs, $S_0M_0L_0$. This was the base group. The category, $S_1M_1L_0$, comprised individuals who had soil and water conservation and also grew improved maize varieties. Considering that this group grew two of the three options, they are considered adopters of SAPs. The group that practiced soil and water conservation and also intercropped but did not grow improved maize varieties was also a group of adopters, $S_1M_0L_1$, however it did not have a lot of observations. Noteworthy, 73 percent of farmers in the sample used inorganic fertilizers. Since the adopters of inorganic fertilizers are relatively higher than non-adopters, creating a combination that includes inorganic fertilizers as an option spreads the observations in the sample too thinly. So to construct a variable that would be used as a dependent variable in the multinomial logit model, we use the combinations that had observations greater than ten percent as standalone alternatives while the aforementioned rare options, i.e. groups 2,4,6 and 7 adopters (group eight) respectively since they adopted at least one choice. Resultant, we have a dependent variable that has four choices which are summarized in Table 2.

<<TABLE 1 ABOUT HERE>>

<<TABLE 2 ABOUT HERE>>

Table 3 presents the descriptive statistics of the variables that were used in the multinomial regression. Using Analysis of Variance (ANOVA) techniques, the table presents a summary of *F*-test comparisons of means between adopters and non-adopters in the resultant three classes of SAPs. Results indicate that the demographic characteristics are systematically different between the adoption strategies. The average age of the household head was 45 years old of which 88 percent were males. Most of the household heads had done five years of formal schooling. The average household size was six members.

<<TABLE 3 ABOUT HERE>>

Plot characteristics were also systematically different. For instance, it takes 23 minutes. About 90 percent of all plots were household owned i.e. customary land and ten percent were rented. On average a household applied four bags and 74 percent used inorganic fertilizers. Perceptions concerning fertilizers varied across farmers who practiced different intensification strategies. Chi-square test statistics were reported significant indicating that farmers perceived that their soils were different across the slopes. About 14 percent perceived that their soils were fertile, 44 percent indicated that their soils were moderately fertile while 43 percent perceived that their soils were not fertile at all. Chi-square statistics for the slope of the soil where also statistically significant indicating that farmers' perceptions on plot slopes varied. About 47 percent of households in the sample perceived that their plots were on steep slopes while 41 percent perceived that their slopes were medium slope.

4. Empirical results

Table 4 presents a summary of the multinomial logistic regression model. In general, the model fit with a log-likelihood statistic of -2033.04 and with a Wald Chi-square test statistic of 100.17 with 39 degrees of freedom, we rejected the null hypothesis that the fitted model was statistically equivalent to a null model which had a log-likelihood of -1440.58 with a 99 percent level of confidence.

<<TABLE 4 ABOUT HERE>>

Results indicate that household characteristics affect adoption of various SAPs. For instance, in the soil and water conservation category $(S_1M_1L_0)$, if the head attended an additional year of formal schooling, the log of odds would change by 0.09 as compared to non-adopters. If the household head adopted all the technologies and was one additional year older than the average age, the log of odds against non-adopters, $S_0M_0L_0$, would be 0.14. If the household added one more member in the first category, $(S_1M_1L_0)$, then the log of odds against non-adopters would decrease by 0.12. In the third category, $(S_1M_1L_1)$, the log of odds would decrease by 0.08.

Plot characteristics vary with adoption of various strategies. For instance, when farmers perceive that their plot is fertile, the log of odds of adopting strategy 1, $S_1M_1L_0$, reduces by 0.49 while when the soil is moderately fertile, the log of odds increases by 0.42 this is also similar when all technologies are adopted i.e. it increases the log of odds by 0.48 . If the soils are fertile, the log of odds of adopting improved maize varieties reduces by 0.57. If the soils are fertile, the log of odds of adopting all technologies reduces by 0.55. Further, if the plot is flat, then the log of odds of adopting all technologies reduces by 1.07.

Generally, these results indicate that adoption of intensification strategies varies with household characteristics. Further, plot characteristics are also a major determinant of adoption of sustainable intensification strategies. That is, if farmers perceive that a farm is fertile they are less likely to adopt intensification strategies than otherwise. In addition, if farmers perceive that their farm is on a flat ground, they are also less likely to adopt sustainable intensification strategies.

4.1. Average adoption effects for a combination of intensification strategies

Results of the multinomial endogenous switching regression for output are summarized and reported in Table 5. With a log likelihood of -5743.54 and the Wald Chi-square statistic equal to 269.26 with 38 degrees of freedom, we rejected the null hypothesis that the model was statistically equal to a null model and concluded that the model fit correctly with a 99 percent level of confidence. This is also evidenced by the number of statistically significant explanatory variables in the model. Coefficients of two selection variables are statistically significant. Significance in this case implies that intensification strategies effects would not be the same for non-adopters had it been that they had adopted.

<<TABLE 5 ABOUT HERE>>

Results from the Average Treatment effects on the Treated (ATT) indicate that households that adopted soil and water conservation technologies ($S_1 M_1 L_o$) were 23 percent more farm output than non-adopters. This result corroborates with Ngwira et al. (2014) who found positive effects of soil and water conservation on output. Results further suggest that households that adopted all technologies considered had statistically lower yields than non-adopters. This result suggests that there are trade-offs in the sustainable intensification technologies such that when taken as an entire bundle, they could reduce farm output. This outcome supports Giller et al. (2009) who also found that there might be trade-offs in the technology bundles that intensification strategies such as conservation agriculture propose. Further, Kassie et al., (2013) also found that there could be complementarities and trade-offs in sustainable agricultural practices. Considering that farmers are usually rational beings, they tend to adopt technologies that present complementarities rather than technologies that have trade-offs.

We failed to reject the hypothesis that the ATT for adopters of improved maize seed only was statistically not different from zero. This could suggest that most farmers (85 percent) adopted improved maize and there was barely variation in the outcome. Kennedy (2008) indicates that substance should take precedence over statistical significance. In this case, results suggest that most farmers adopted improved maize seed and as such their outcomes might not be statistically different. This result also supports Ricker-Gilbert and Chirwa (2011) who observed that in as much as the subsidy program in Malawi seems to target all farmers, it benefits a wide range of farmers regardless of farm size.

Table 6 summarizes results of the MESR for farm income. Results generally indicate that the model fit correctly with a log likelihood of -6612.34 with a Wald Chi-square statistic of 206 .20 which was statistically significant at a 99 percent level of confidence. The results suggest that the model fit correctly. Two of the coefficient of the selection variables are statistically significant indicating that non-adopters could have different effects had it been that they adopted sustainable agricultural practices.

<<TABLE 6 ABOUT HERE>>

With regard to farm incomes, results indicate some similarities to the farm output results. In general, results indicate that farming households that adopted soil and water conservation together with improved maize had statistically higher incomes than non-adopters. We also find that households that adopted all technologies had statistically lower incomes than farmers that adopted parts of the sustainable agricultural practices. We similarly fail to reject the null hypothesis that farmers that adopted improved maize only had statistically more income than non-adopters for the same aforementioned reason. The results on farm incomes indicate that farming households that practiced all the technologies realized significantly less incomes than non-adopters.

In order to triangulate the MESR results, Table 7 summarizes results of the propensity score matching results on output. The PSM results passed balancing and common support tests. In general, results from PSM indicate similar ATTs with the MESR model. Since the pattern is similar in impacts, results for incomes have been omitted but are available upon request. Considering that results from the two methods present similar findings, we can conclude that the direct causal effects obtained are correct.

<<TABLE 7 ABOUT HERE>>

Impacts vary by geographical location. Table 8 summarizes the geographical distribution of the treatments while Table 9 the impacts of SAPs adoption. Further, when distributed by geographical location, the ATTs indicate that Mchinji, Kasungu and Ntcheu had positive significant differences for farmers that adopted improved maize and practiced soil and water conservation. However, for farmers that practiced improved maize farming alone, the ATTs were consistently not significant in most locations except in Kasungu where impacts were negative and significant at 10 percent and Ntcheu where positive impacts were observed at 10 percent significance level. In terms of adopting all technologies, in Ntcheu we found that it significantly reduced output with 95 percent level of confidence. These results suggest a cautionary tale to what Kirkgaard (2013) indicated that intensification strategies should not be adopted in isolation. Our findings add that adopting farmers should consider carefully what works and what does not because adopting too many technologies at once may reduce output.

<<TABLE 8 ABOUT HERE>>

<<TABLE 9 ABOUT HERE>>

The results presented above have considerable implications. First, practicing sustainable intensification strategies results in increased farm output. Considering that small holder farming households integrate decisions of production, consumption, future production and trade into one institution (Sadoulet & de Janvry, 1995), increased farm output means more food for home consumption. Further accounting for the semi-commercialized nature of the households, the surplus after accounting for home consumption needs might be sold for extra income for the household. Since SAP adopting households have significantly more incomes than non-adopting households, it can be inferred that one of the lasting solutions to household incomes lies within SAPs. Second, it has been consistently observed that SAPs have negative effects when they are adopted in totality without accounting for trade-offs and complementarities. Farmers should be encouraged to adopt intensification strategies that work in a particular location to avoid adopting too many strategies that may end up competing among themselves for resources. Third, results have shown no statistical differences between adopters and non-adopters of improved maize because over two thirds of households in the sample used improved seed. This is a direct result of the input subsidy program which the Government of Malawi has been implementing. It suggests that farmers in the sample have more access to seed (Dorward & Chirwa, 2011). Access to improved seed is encouraged for continued growth of the agricultural sector. Third, household characteristics were statistically significant in the adoption of SAPs. It is thus important to tailor extension messages about sustainable intensification for audiences of different gender, ages and educational backgrounds since their levels of comprehension and adoption might be different. Fourth, farmers' perceptions of the characteristics of their plots are key to adoption of sustainable agricultural practices. However, regardless of soil and slope characteristics of the soil, it is important to practice sustainable intensification strategies since the art of farming involves mining resources which might become exhausted if sustainable practices are used.

5. Concluding remarks

Sustainable agricultural practices and uptake of technology have been promoted by governments in developing countries for decades. However, it seems that overtimes, farmers still do not adopt other technologies than others. Research has then been riddled with mixed results of these technologies with others holding the extreme that some strategies are detrimental for farmers while others indicating that the intensification strategies are a beneficial package. In this study, we evaluate determinants of sustainable agricultural practices adoption and draw direct causal effects of SAPs on farm output and incomes. We use a multinomial logistic regression model to assess determinant of SAPs adoption in the first stage. In the second stage we use the multinomial endogenous switching regression framework to evaluate direct causal effects of SAPS on farm output and farm incomes. In general, our results indicate that household characteristics determined which strategies would be adopted. These included gender, age and education of the household head. Further, plot characteristics also influenced the decision to adopt sustainable agricultural practices. These included perceptions on soil fertility; slope; whether they used inorganic fertilizers and walking distance to the plot. These results on adoption of sustainable practices can be used to inform government and private extension systems in developing strategies that could help improve technology adoption.

With regard to direct causal effects of SAPs adoption and technology adoption, we find that farmers that adopt soil and water conservation and improved maize technologies have positive incomes. Further, of farmers who adopted all sustainable agricultural practices realized less farm incomes. These results imply that extension messages should be tailored to assist farmers adopt technologies which are suitable to them instead of adopting all technologies.

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List of tables

Table 1: Possible Sustainable Intensification strategies that smallholder maize farmers practice

Choice (j)	Strategy	Soil and Water Conservation (S)		Improved maize variety (M)		Legume Intercropping (L)		Frequency (%)
		S_1	S_0	M_1	M_0	L_1	L_0	
1	$S_0M_0L_0$		✓		✓		✓	26.22
2	$S_1M_0L_0$	✓			✓		✓	0.46
3	$S_0M_1L_0$		✓	✓			✓	15.00
4	$S_0M_0L_1$		✓		✓		✓	0.85
5	$S_1M_1L_0$	✓		✓			✓	48.49
6	$S_1M_0L_1$	✓			✓	✓		4.41
7	$S_0M_1L_1$		✓	✓		✓		1.39
8	$S_1M_1L_1$	✓		✓		✓		3.17

Table 2: Possible Sustainable Intensification strategies that smallholder maize farmers practice

Choice (j)	Strategy	Soil and Water Conservation (S)		Improved maize variety (M)		Legume Intercropping (L)		Frequency
		S_1	S_0	M_1	M_0	L_1	L_0	
1	$S_1M_1L_0$	✓		✓			✓	43.26
2	$S_0M_1L_0$		✓	✓			✓	21.54
3	$S_1M_1L_1$	✓		✓		✓		9.43
4	$S_0M_0L_0$		✓		✓		✓	25.77

Table 3: Descriptive statistics for covariates used in regression

Variables	$S_1M_0L_0$	$S_0M_0L_1$	$S_1M_0L_1$	$S_0M_1L_1$	Mean	SD	Test stat	Sig.
Household characteristics								
Age of head	44.90	45.24	46.68	47.82	45.48	14.25	2.65	**
Gender of head (Male=1)	89.89	86.47	84.54	88.14	88.21		6.65	*
Education of head (years)	5.46	5.32	4.89	6.09	5.42	3.51	3.90	***
Household size	5.87	6.09	6.07	6.40	6.00	2.26	56.48	***
Plot characteristics								
Distance to the plot (minutes)	22.02	24.84	22.36	23.57	22.95	30.36	121.62	***
Tenure								
Owned	92.53	82.88	93.24	91.53	90.00		38.87	***
Rented	6.53	16.07	6.28	7.34	10.00			
Inorganic fertilizer applied (NPK+UREA) (50kg bags)	4.30	4.18	4.05	4.40	4.25	1.08	3.61	***
Inorganic fertilizer users (Yes=1)	73.79	71.46	73.91	84.18	74.21		11.16	***
Soil Fertility								
Fertile	12.84	12.08	20.29	13.64	13.57		12.84	**
Medium	45.47	43.86	41.06	38.07	43.82			
Not fertile	41.68	44.07	38.65	48.30	42.60			
Soil slope								
Flat slope	47.89	49.36	34.78	56.25	47.59		24.40	***
Medium slope	41.58	39.62	46.86	32.95	40.83			
Steep slope	10.53	11.02	18.36	10.80	11.58			
No. obs.	2196							

Notes:
*Significant at the 10% level
**Significant at the 5% level
***Significant at the 1% level
F-test and chi-square are used for continuous and categorical variables, respectively.

Table 4 Parameter estimates of adoption of sustainable intensification strategies – multinomial logistic regression

VARIABLES	(1) Field has SWC and improved maize $S_1M_1L_0$		(2) Improved maize only $S_0M_1L_0$		(3) All technologies $S_1M_1L_1$	
Household characteristics						
Gender of the head	0.4211	(0.2754)	-0.0678	(0.2897)	0.0513	(0.3315)
Age of the head	0.0524	(0.0400)	0.0151	(0.0427)	0.1396***	(0.0513)
Age squared	-0.0007*	(0.0004)	-0.0003	(0.0004)	-0.0015***	(0.0005)
Education of head	0.0893***	(0.0253)	0.0901***	(0.0274)	0.1191***	(0.0329)
Household size	-0.1184***	(0.0376)	-0.0532	(0.0395)	-0.0841*	(0.0475)
Plot characteristics						
Distance to the plot (mins)	-0.0029	(0.0020)	-0.0002	(0.0023)	-0.0037	(0.0028)
Tenure (Customary=1)	-0.2289	(0.3169)	0.7883**	(0.3179)	-0.1762	(0.4157)
Soil fertility						
Fertile	-0.4910**	(0.2201)	-0.5690**	(0.2305)	-0.5451**	(0.2655)
Medium	0.4201**	(0.1852)	0.3098	(0.1992)	0.4836**	(0.2343)
Soil slope						
Flat slope	-0.1911	(0.2864)	-0.1364	(0.3051)	-1.0686***	(0.3324)
Moderate	0.2630	(0.2936)	0.2204	(0.3116)	-0.1064	(0.3312)
Constant	2.0153*	(1.1438)	2.0963*	(1.2083)	-0.9577	(1.4221)
Log likelihood	-2033.04***					
Observations	2196		2196		2196	

Notes: Robust standard errors in parentheses on sideway
Non-adopters $S_0M_0L_0$ is the base category
*Significant at the 10% level
**Significant at the 5% level
***Significant at the 1% level

Table 5: Results of multinomial endogenous Switching regressions showing (ATT) for farm output

Variables	(1) Field has SWC and improved maize $S_1M_1L_0$		(2) Improved maize only $S_0M_1L_0$		(3) All technologies $S_1M_1L_1$		(4) Output	
Household characteristics								
Gender of head	0.2754	(0.2076)	-0.2623	(0.2274)	-0.1350	(0.2724)	0.3971***	(0.0648)
Age of head	0.0350	(0.0280)	-0.0113	(0.0316)	0.1111**	(0.0444)	0.0332***	(0.0090)
Age squared	-0.0006**	(0.0003)	-0.0001	(0.0003)	-0.0012***	(0.0004)	-0.0003***	(0.0001)
Education of head	-0.0248	(0.0193)	-0.0257	(0.0222)	-0.0589**	(0.0289)	0.0293***	(0.0060)
Household size	-0.0577**	(0.0285)	0.0225	(0.0319)	-0.0141	(0.0416)	0.0092	(0.0094)
Plot characteristics								
Inorganic fertilizer adoption	0.1376	(0.1433)	-0.0213	(0.1625)	0.1460	(0.2018)		
Soil fertility								
Fertile	0.4718**	(0.2043)	0.2603	(0.2363)	1.0481***	(0.2615)		
Medium	0.3487***	(0.1338)	0.1761	(0.1539)	0.4435**	(0.1967)		
Soil slope								
Flat	-1.0935***	(0.2612)	-1.0340***	(0.2856)	-2.4000***	(0.3096)		
Moderate	-0.7941***	(0.2647)	-0.8465***	(0.2900)	-1.3094***	(0.3032)		
Average Treatment Effect on the Treated								
$S_1M_1L_0$							0.2306***	(0.0629)
$S_0M_1L_0$							0.0309	(0.0893)
$S_1M_1L_1$							-0.8336***	(0.0730)
Constant	1.0190	(0.7301)	1.3780*	(0.8160)	-1.8566*	(1.1046)	4.8458***	(0.2238)
lnsigma	-1.4148***	(0.2888)						
lambda_category1	-0.1594***	(0.0499)						
lambda_category2			-0.0567	(0.0917)				
lambda_category3					0.8763***	(0.0271)		
Observations	2,196		2,196		2,196		2,196	

Notes: Robust standard errors in parentheses on sideway
Non-adopters $S_0M_0L_0$ is the base category in the multinomial treatment effects regression
*Significant at the 10% level
**Significant at the 5% level
***Significant at the 1% level

Table 6: Results of multinomial endogenous Switching regressions showing (ATT) for income

Variables	Field has SWC and improved maize $S_1M_1L_0$		Improved maize only $S_0M_1L_0$		All technologies $S_1M_1L_1$		Output	
Household characteristics	0.2925	(0.2073)	-0.2539	(0.2270)	-0.1951	(0.2773)	0.3203***	(0.1018)
Gender of head	0.0349	(0.0280)	-0.0119	(0.0316)	0.1168***	(0.0452)	0.0280**	(0.0141)
Age of head	-0.0006**	(0.0003)	-0.0001	(0.0003)	-0.0013***	(0.0004)	-0.0002*	(0.0001)
Age squared	-0.0242	(0.0194)	-0.0268	(0.0223)	-0.0590**	(0.0288)	0.0267***	(0.0096)
Education of head	-0.0577**	(0.0284)	0.0256	(0.0320)	-0.0077	(0.0420)	0.0242*	(0.0144)
Household size								
Plot characteristics	0.1353	(0.1431)	-0.0153	(0.1623)	0.0727	(0.2094)		
Inorganic fertilizer adoption	0.4630**	(0.2048)	0.2370	(0.2352)	1.1157***	(0.2705)		
Soil fertility	0.3409**	(0.1338)	0.1724	(0.1534)	0.3751*	(0.2017)		
Fertile	-1.1037***	(0.2613)	-1.0855***	(0.2854)	-2.1548***	(0.3179)		
Medium	-0.7942***	(0.2647)	-0.8725***	(0.2898)	-1.2328***	(0.3136)		
Average Treatment Effects on the Treated								
$S_1M_1L_0$							0.4542***	(0.1154)
$S_0M_1L_0$							-0.1536	(0.1295)
$S_1M_1L_1$							-0.3377**	(0.1323)
Constant	1.0167	(0.7306)	1.4111*	(0.8152)	-2.0290*	(1.1209)	9.1802***	(0.3528)
lnsigma	0.2915***	(0.0216)						
lambda_category1	-0.2783***	(0.1030)						
lambda_category2			0.1530	(0.1096)				
					0.4585***	(0.0708)		
Observations	2,196		2,196		2,196		2,196	

Notes: Robust standard errors in parentheses on sideway

Non-adopters $S_0M_0L_0$ is the base category in the multinomial treatment effects regression

*Significant at the 10% level

**Significant at the 5% level

***Significant at the 1% level

Table 7: Average Treatment Effect on the Treated (log of output)

	$S_1M_1L_0$	$S_oM_1L_0$	$S_1M_1L_1$
ATT	0.204 (0.050)***	-0.094(0.060)*	-0.086 (0.081)
Balancing test satisfied	Yes	Yes	Yes
Common support imposed	Yes	Yes	Yes
Treated	945	466	206
Control	1,224	1,703	1,963
Sample size (n)	2,196	2,196	2,196

Note: Nearest Neighbour Matching Techniques Used
Standard errors in parentheses on the sideway

Table 8: Geographical distribution of the SAP choices

treatments	$S_1M_1L_0$	$S_oM_1L_0$	$S_1M_1L_1$	$S_1M_1L_1$	Total
Lilongwe	39.47	35.1	37.68	32.33	36.52
Mchinji	8	12.26	3.38	5.12	7.74
Kasungu	18.95	18.6	10.14	27.21	20.17
Salima	9.58	11.21	1.93	11.13	9.61
Ntcheu	11.05	8.03	26.57	10.42	11.7
Balaka	12.95	14.8	20.29	13.78	14.25
Sample size (n)	950	473	207	566	2,196

Table 9: Geographical Distribution of Average Treatment Effects on the Treated (ATT) in terms of output

Location	$S_1M_1L_0$	$S_oM_1L_0$	$S_1M_1L_1$	n
Lilongwe	0.086 (0.814)	-0.195(0.097)	0.062(0.125)	794
Mchinji	0.336(0.180)***	-0.118(0.186)	0.166(0.381)	170
Kasungu	0.326(0.123)***	-0.223(0.157)*	-0.086(0.257)	433
Salima	-0.046(0.165)	0.499(0.168)	0.259(0.189)*	208
Ntcheu	0.347(0.148)***	0.302(0.226)*	-0.325(0.188)**	257

Balaka	0.053(0.124)	-0.111(0.132)	-0.041(0.151)	307

Note: Propensity Score Matching using nearest neighbor matching used
Standard errors in parentheses on the sideway

Equations

Equation – The style is named Equation,

Footnotes

Footnotes should be used sparingly. Please use 10-points Times New Roman. In many cases it will be possible to incorporate the information in normal text. If used, footnotes should be numbered in the text, indicated by superscript numbers, and kept as brief as possible. Equations or other complex text should not appear in footnotes, since they will be difficult to read.

Tables and Figures

Collect references, tables and figures, in that order, at the end of the manuscripts. Tables & figures should be numbered consecutively and their position in the text must be indicated.

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