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Maize and legume technology adoption in Malawi: Gender, social networks and SIMLESA effects

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Abstract

This article investigates whether gender, social networks and being a SIMLESA beneficiary plays an important role in determining the level of maize and legume technology adoption. In order to do so, we exploit variation in random cross section data from 731 households in 2014. We use a multivariate probit regression model to analyze adoption of multiple technologies. Our approach allows sequential and simultaneous technology adoption and unobserved factors to be freely correlated across different technology practices. Our results unambiguously show that gender, social networks and being a SIMLESA beneficiary play a significant role.

JEL classifications:

Keywords: adoption; gender; social networks; technology; SIMLESA

1. Introduction

Many Sub-Saharan countries see adoption of modern agricultural technology as an opportunity to promote agricultural development. Malawi for example, has put technology adoption as one of the key drivers of its agricultural sector wide approach. It is believed that technology adoption will increase farm output, improve food security and eventually result in rising household incomes through increased tradable surplus (Government of Malawi, 2011). Evidence suggests that technology adoption can indeed accelerate agricultural growth. In Tanzania for example, Amare et al. (2012) find that maize/pigeon pea adoption has a positive and significant effect on incomes. This supports the widely held view that technology adoption increases household incomes.

Technology adoption is often countered by the uncertainty of the timing when positive impacts start to be realized. Giller et al. (2009) reported that some farmers who later adopted conservation agriculture, ended up with negative returns in the first years. As such most technologies are disseminated to farmers in bundles i.e. a technology package containing a number of interventions aimed to increase productivity. This approach gives farmers the ability to adapt the technologies to suit their own circumstances (citation). For example, female headed households which are labor constrained tend to adopt technologies that demand less labor. Women tend to play an important role in facilitating adoption of knowledge intensive technologies (citation). Furthermore, farmers that are beneficiaries of particular projects tend to adopt new technologies faster than non-beneficiaries (citation).

Adoption packages results in adopting packages that have possible complementarities and tradeoffs. Farmers may adopt all the technologies in the package or may partially adopt. In evaluating adoption of these technologies, it is necessary to take into account the simultaneous or sequential decision making process and the possible trade-offs associated with these technologies. Moreover, agriculture is area specific and farmer adoption behaviour changes according to circumstances. As such, adoption of technology should be analyzed taking into account area specific characteristics and farmer specific circumstances. To illustrate the merits of such analysis, we develop a multivariate probit regression model of farmers who adopted maize/legume intensification technologies taking into account the structure of social networks, gender dynamics and the effect of being a beneficiary in the Sustainable Intensification of Maize based Legume Systems (SIMLESA) project. The model takes into account how various technologies relate with each other by providing a covariance matrix with correlation coefficients. Section 2 outlines data sources and econometric approaches used; section 3 presents results and section 4 outlines conclusions.

2. Methodology

2.1. The model

Agricultural technologies for sustainable intensification usually come in packages. Usually farmers adopt part or complete packages. Adoption of mix of strategies makes dealing with multiple production constraints a lot easier. Of note technologies might be adopted simultaneously and/or sequentially as complements, substitutes or supplements and hence are interdependent (Kassie et. al. 2009). Noteworthy, independent estimation of technologies might lead to biased estimates since it ignores the tradeoffs and complementarities across different technologies (Capellari and Jenkins, 2003). In this study we use a multivariate probit regression model to analyze technology adoption. Multivariate probit models allow error terms (unobserved/unknown factors) to be freely correlated across different practices (Kassie et al.2013). Following Cappellari and Jenkins (2003) the M-equation multivariate probit model is structured as follows.

$$y_{im}^{*} = \beta_m{}'X_{im} + \epsilon_{im}, m = 1, \ldots, M$$

$$y_{im}^{*} = 1 \; if \; y_{im}^{*} > 0 \; and \; 0 \; otherwise \tag{1}$$

$\epsilon_{im}, m = 1, \ldots, M$ are error terms distributed as multivariate normal, each with a mean of zero, and variance-covariance matrix V, where V has value of 1 on the leading diagonal and correlations $\rho_{jk} = \rho_{kj}$ as off diagonal elements. Positive correlation indicates synergies between practices. Negative correlation indicates the existence of tradeoffs (Kassie et al. 2009). The multivariate probit model has a structure like the Seemingly Unrelated Regression (SUR), except that the dependent variables are binary indicators. The y_{im} might represent outcomes for M different choices at the same point in time, for example, whether a farmer adopts M technologies. The X_{im} is a vector of explanatory variables and β_m are unknown parameters to be estimated. The probability function of the probit model is usually the standard normal density which provides predicted values within the range (0, 1).

The multivariate probit model is estimated by simulated maximum likelihood. The log-likelihood function for a sample of N independent observations is given by

$$L = \sum_{i=1}^{N} w_i \log \Phi_m\,(\mu_i; \Omega) \tag{2}$$

where w_i is an optional weight for observation $i = 1, \ldots, N$, and $\Phi_m(.)$ is the multivariate standard normal distribution with arguments μ_i and Ω where $\mu_i = (K'_{im}X_{im})$ with $K_{ik} = 2y_{ik} - 1$, for each I $k = 1, \ldots, m$. Matrix Ω has constituent elements Ω_{jk} where

$$\Omega_{jj} = 1 \; for \; j = 1, \ldots, m$$

$$\Omega_{21} = \Omega_{12} = K_{i1}K_{i2}\rho_{21}$$

$$\Omega_{31} = \Omega_{13} = K_{i3}K_{i1}\rho_{31}$$

$$\Omega_{jk} = \Omega_{kj} = K_{im}K_{im-1}\rho_{mm-1}$$

As shown the log-likelihood function depends on the multivariate standard normal distribution function $\Phi_m(.)$. In this research, the Geweke–Hajivassiliou–Keane (GHK) smooth recursive conditioning simulator will be applied to evaluate the multivariate normal distribution function (Borsch-Supan *et al.* 1992; Borsch-Supan and Hajivassiliou, 1993; Keane, 1994; and Hajivassiliou and Ruud, 1994). The GHK simulator exploits the fact that a multivariate normal distribution function can be expressed as the product of sequentially conditioned univariate normal distribution functions, which can be easily and accurately evaluated.

2.2.Data and descriptive statistics

The study uses data collected by the LUANAR/CIMMYT Adoption Pathways Project. The survey data used is comprehensive and contains various technologies provided by the SIMLESA project. The aim of the SIMLESA project is to understand smallholder farmers' decision making processes about their farming practices and adoption of technology. The project seeks to view adoption of technology within farmers' socioeconomic circumstances. 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.

Table 1 presents descriptive statistics of the variables used in the model. The variables have first been grouped into two categories namely dependent and explanatory variables. The dependent variables consist of dummy variables indicating adoption of a particular technology. Adoption of technologies is low in most categories. Improved variety adoption is the highest with an adoption of 70 percent among the respondents. It is seconded by chemical fertilizer application which is adopted by 53 percent of the respondents. Other technologies were adopted by less than 50 percent of the individuals interviewed.

Explanatory variables are grouped into socioeconomic characteristics, plot characteristics and location specific dummy variables. Selection of variables follows previous adoption studies such as Feder et al. (1985), Chirwa (2005), Lee (2005), Knowler & Bradshaw (2007), Kassie et al. (2009), Arslan et al. (2013), Handschuch & Wollni 2013, Kassie et al. (2013), Teklewold et al. (2013). The model assumes that the adoption decision is influenced by socioeconomic circumstances of farmers. Male headed households predominated the sample space with a proportion of 0.87. The average age of the household head was 46 years old and the head had done about 5 years of formal education. The proportion of married household heads in the sample was 0.86 and the gap between education status of female and male spouses was -1.12 which means that male spouses were most likely a year ahead of their spouses in education. On average, three individuals were actively involved in providing labor for the household.

Table 1 Definition of variables and descriptive statistics

Dependent variables		**Mean**	**Std.Dev.**
Intercropping (IC)	Plots received legume intercropping (1=yes; 0=no)	0.17	0.38
Crop rotation (CR)	Plots received maize-legume rotation (1=yes; 0=no)	0.31	0.46
Residue cover (RC)	Plots received 30% residue cover (1=yes; 0=no)	0.21	0.41
Soil and stone bunds	Plots received soil and stone bunds (1=yes; 0=no)	0.30	0.46

(SSB)			
Box ridges (BR)	Plots received box ridges (1=yes; 0=no)	0.41	0.49
Manure	Plots received animal manure (1=yes; 0=no)	0.18	0.39
Chemical fertilizer (CF)	Plots received chemical fertilizer (1=yes; 0=no)	0.53	0.50
Improved variety (IV)	Plots received improved variety (1=yes; 0=no)	0.74	0.44
Explanatory variables		**Mean**	**Std.Dev.**
Socioeconomic characteristics			
gender_head	Gender of the household head (1=male; 0=female)	0.87	0.34
age_head	Age of the household head (years)	46.39	14.60
edu_head	Education of the household head (years of schooling)	5.38	3.53
nosingle	Household head is married (1=yes; 0=no)	0.86	0.34
edu_gap	Education difference between female spouse and male head (years)	-1.12	3.25
activelabor	Number of persons participating in farm work (number)	2.71	1.05
mexperience	Experience with improved maize seeds (years)	3.03	3.47
lexperience	Experience with improved legume seeds (years)	4.09	4.61
farmgroup	Participation in farmer's group (1=yes; 0=no)	0.15	0.36
credass	Participation in credit association (1=yes; 0=no)	0.39	0.49
SIMLESA	EPA of the household was targeted by SIMLESA (1=yes; 0=no)	0.18	0.38
total_land	Total farm size (acre)	4.45	4.02
fertavail	Fertilizer availability is a problem (1=yes; 0=no)	0.45	0.50
drought	Drought within the last ten years (1=yes; 0=no)	0.52	0.50
pest	Pests within the last ten years (1=yes; 0=no)	0.24	0.43
crpdam_lst	Livestock crop damage within the last ten years (1=yes; 0=no)	0.15	0.36
Plot characteristics			
plotsize	Plot size (acre)	1.07	1.07
plotdistance	Plot distance to dwelling (walking minutes)	23.38	30.15
tenure	Plot ownership (1=owned; 0=otherwise)	0.90	0.30
pm_male	Plot managed by man (1=yes; 0=no)	0.41	0.49
pm_female	Plot managed by woman (1=yes; 0=no)	0.28	0.45
pm_both (ref.)	Plot managed by jointly by man and woman (1=yes; 0=no)	0.31	0.46
slope	Farmer's perception that plot has flat to moderate slope (1=yes; 0=no)	0.67	0.47
fertility	Farmer's perception that plot has good to moderately fertile soil (1=yes; 0=no)	0.72	0.45
depth	Farmer's perception that plot has shallow to moderately deep soil (1=yes; 0=no)	0.74	0.44
District dummies			
Lilongwe	Lilongwe district (1=yes; 0=no)	0.38	0.49
Mchinji	Mchinji district (1=yes; 0=no)	0.09	0.28
Kasungu	Kasungu district (1=yes; 0=no)	0.19	0.40
Salima	Salima district (1=yes; 0=no)	0.09	0.28
Ntcheu	Ntcheu district (1=yes; 0=no)	0.13	0.33
Balaka (ref.)	Balaka district (1=yes; 0=no)	0.13	0.33
Number of plot observation	1847		

Respondents indicated that they had at least four years' experience cultivating improved legume seed and had three years' experience cultivating improved maize seed. Over 15 percent of respondents indicated that they belonged to a farming club. About 18 percent of households participated in agricultural credit association. Further, 18 percent of the households indicated that they were in SIMLESA targeted Extension Planning Areas (EPA). The average land holding size was 4 hectares. About 45 percent of farmers indicated that accessing fertilizer was a problem. About 52 percent of respondents reported that they had experienced a drought within ten years. About 24 percent of farmers indicated that they experienced problems with pest while 15 percent reported that they had problems with livestock damaging their crops.

The study also considered plot characteristics. The average plot size was one acre and it took a representative farmer 23 minutes to get to it. About 90 percent of the plots cultivated are owned by the household head and 40 percent are managed by men, 28 percent by women and 31 percent by both men and women. About 67 percent of the plots were reported flat to moderate in slope and 70 percent reported that they had good to moderately fertile soils. Noteworthy, 74 percent of households reported that the plot soils were shallow to moderately deep soils. Geographically, the data was collected in six districts namely Lilongwe, Mchinji, Kasungu, Salima, Ntcheu, and Balaka. Respective proportions are reported in Table 1. In total, there were about 1847 plots.

3. Results and discussion

3.1.Model fitness and independence of technologies

This section discusses results of the multivariate probit regression model. Of note, the regression was estimated at plot level. The hypothesis of independence of the disturbance terms associated with the technologies was strongly rejected with a likelihood ratio test ($\chi^2_{28} = 347.33, p < 0.001$). The likelihood ratio test indicates that the adoption of different CA technologies is not mutually exclusive and independent of other technologies, which supports use of multivariate probit model. Table 2 presents results of the binary correlations between error terms of the technologies in question. Results indicate that some technologies are complements while others are substitutes.

Table 2
Rho- matrix: Correlation coefficients for MVP regression equations (standard errors in parentheses)

	ρIC	**ρCR**	**ρRC**	**ρSSB**	**ρBR**	**ρmanure**	**ρCF**
ρCR	0.29 (0.044)***						
ρRC	0.20 (0.050)***	0.06 (0.045)					
ρSSB	0.17 (0.047)***	0.10 (0.042)**	0.33 (0.042)***				
ρBR	0.05 (0.045)	0.14 (0.039)***	0.07 (0.044)*	-0.03 (0.041)			
ρmanure	0.16 (0.051)***	-0.15 (0.048)***	0.02 (0.052)	0.15 (0.046)***	0.06 (0.045)		
ρCF	0.31 (0.044)***	-0.07 (0.040)*	-0.09 (0.045)*	0.10 (0.041)**	0.10 (0.038)***	0.36 (0.042)***	
ρIV	0.32 (0.050)***	0.03 (0.043)	0.12 (0.047)**	0.13 (0.044)***	-0.01 (0.041)	0.09 (0.049)*	0.08 (0.040)**

Likelihood ratio test of:
ρCRIC=ρRCIC=ρSSBIC=ρmanureIC=ρCFIC=ρIVIC=ρRCCR=ρSSBCR=ρBRCR=ρmanureCR=
ρCFCR=ρIVCR=ρSSBRC=ρBRRC=ρmanureRC=ρCFRC=ρIVRC=ρBRSSB=ρmanureSSB=ρCFSSB=ρIVSSB=
ρmanureBR=ρCFBR=ρIVBR=ρCFmanure=ρIVmanure=ρIVCF=0
Chi2(28) = 347.33***

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

Of note, significant trade-offs occur in the fertility enhancing technologies such as manure-CR and CF-CR. This might be an indication that these technologies are substitutes. This is not a surprising result as Khakbazan et al. (2006) indicated that chemical fertilizers might have a substituting relationship with crop rotation strategies. Teklewold et al. (2013) also find that manure and crop rotation are used as substitutes. Marenya and Barrett (2007) found manure and chemical fertiliser to be complementary, but a supplementary use (Teklewold et al. 2013) would also make sense. It probably depends on the availability of fertilizer and household capital to purchase chemical fertilizer. Crop rotation strategies usually use legumes to follow grass family crops so that the legumes might provide nitrogen for the grass families that follow. However, if chemical fertilizers are readily available it becomes easy to substitute them.

Further, RC-IC, manure-IC, CF-IC, manure-CF, IV-IC show positive results indicating that there are complementarities between the technologies. Hoorman (2009) indicated that residue cover can have some benefits on crops whether intercropped or standalone. It may provide much needed moisture and nutrients to crops. Furthermore, since intercropping usually varies different crops with different root depths together, manure and intercropping can have a complementary relationship since crops have different demands (FAO, 2009).

3.2.Adoption of CA technologies

Table 3 presents results of the marginal effects of the multivariate probit model. Results indicate that a number of socioeconomic, plot specific characteristics and location factors had considerable explanatory power on adoption of CA technologies.

3.2.1. Socioeconomic factors

The number of individuals actively participating in labour provision positively influenced intercropping adoption decisions. This is because most small holder farmers are labour constrained and the number of workers in the field significantly conditions adoption of intercropping (Citation). A similar explanation can be provided for the adoption of soil and stone bunds.

Further, results also indicate that farmers who have had experience in growing improved legume varieties were more likely to adopt residue cover and soil and stone bunds and a combination of the two technologies. Nevertheless, farmers that had experience in growing improved maize did not adopt residue cover and stone bunds. This might indicate that some technologies require some experience before farmers adopt.

Membership to farmer associations influences adoption of residue cover positively. Farmers influence each other when they are in groups. As such adoption can be accelerated when farmers are in groups. Farmer groups in the study area were encouraged to utilize residue

Membership to credit associations positively influenced adoption of legume intercropping and residue cover. When farmers have access to credit, they are able to adopt modern technologies which might be resource intensive.

Noteworthy, if the EPA from which the household was sampled is a SIMLESA designated EPA, individuals were more likely to adopt legume intercropping and soil and stone bunds, respectively.

Land holding size negatively influenced adoption of legume intercropping and residue cover. The main reason farmers intercrop is because they face land constraints. However, if farmers have more land the incentive to intercrop becomes less of a problem. However, there might also be an interaction between land and labour constraints. Further, residue cover is labour intensive and bigger land sizes imply more labour to finish laying residue cover. Because of the extra cost of labour associated with more land, farmers do not adopt residue cover.

Table 3

Coefficient estimates of multivariate probit model (standard errors in parentheses)

Explanatory variables	**Dependent variables**			
	Legume intercropping (LI)	Residue cover (RC)	Soil and stone bunds (SSB)	Box ridges (BR)
Socioeconomic characteristics				
gender_head	0.371 (0.276)	-.008 (.244)	.511 (.253)**	.692 (.249)***
age_head	-0.002 (0.003)	.004 (.003)	-.001 (.003)	-.000 (.002)
edu_head	-0.002 (0.015)	-.019 (.014)	-.002 (.013)	.001 (.012)
nosingle	-0.377 (0.261)	.041 (.233)	-.534 (.238)**	-.636 (.239)***
edu_gap	-0.004 (0.014)	.001 (.014)	.035 (.013)***	.019 (.012)
activelabor	0.143 (0.038)***	-.042 (.038)	.093 (.034)***	-.027 (.033)
mexperience	-0.014 (0.011)	-.014 (.011)	-.026 (.010)***	.009 (.009)
lexperience	0.011 (0.009)	.017 (.008)**	.030 (.007)***	-.002 (.007)
farmgroup	0.007 (0.106)	.387 (.095)***	.105 (.091)	.095 (.086)
credass	0.213 (0.078)***	.266 (.074)***	-.007 (.068)	.063 (.064)
SIMLESA	0.189 (0.100)*	.010 (.095)	.165 (.087)*	.035 (.083)
total_land	-0.079 (0.017)***	-.085 (.017)***	.009 (.009)	.008 (.009)
fertavail	0.053 (0.077)	-.235 (.072)***	.539 (.067)***	.144 (.063)**
drought	-0.033 (0.077)	.146 (.072)**	.107 (.067)	-.033 (.063)
pest	0.245 (0.088)***	.489 (.081)***	-.294 (.080)***	-.229 (.075)***
crpdam_lst	0.116 (0.100)	-.420 (.107)***	-.168 (.092)*	.014 (.086)
Plot characteristics				
plotsize	0.270 (0.039)***	-.001 (.053)	-.032 (.043)	-.003 (.033)
plotdistance	-0.001 (0.001)	.001 (.001)	-.004 (.001)**	-.002 (.001)
tenure	-0.046 (0.122)	.283 (.124)**	.408 (.115)***	.219 (.103)**
pm_male	0.089 (0.091)	.052 (.085)	.128 (.078)	.003 (.073)
pm_female	0.196 (0.113)*	-.019 (.106)	.144 (.100)	-.276 (.094)***
slope	-0.125 (0.080)	-.011 (.076)	-.144 (.069)**	.007 (.067)
fertility	-0.004 (0.083)	-.132 (.078)*	-.198 (.071)***	-.293 (.068)***
depth	0.032 (0.087)	.244 (.084)***	.152 (.075)**	.062 (.070)
District dummies				
Lilongwe	-0.504 (0.116)***	.418 (.122)***	.079 (.110)	.087 (.105)
Mchinji	-1.028 (0.184)***	.265 (.158)*	-.243 (.147)*	-.038 (.137)
Kasungu	-0.617 (0.143)***	.199 (.146)	-.034 (.127)	.147 (.120)
Salima	-1.480 (0.235)***	-.005 (.171)	-.208 (.150)	-.248 (.143)*
Ntcheu	0.072 (0.131)	.299 (.145)**	-.072 (.131)	.276 (.124)**
Constant	-.968 (.293)***	-1.316 (.293)***	-1.192 (.268)***	-.279 (.251)

Explanatory variables	**Dependent variables**			
	Crop rotation (CR)	Manure	Chemical fertilizer (CF)	Improved variety (IV)
Socioeconomic characteristics				

gender_head	.310 (.242)	.560 (.265)**	.056 (.223)	.231 (.235)
age_head	-.000 (.003)	-.002 (.003)	-.002 (.002)	-.009 (.003)***
edu_head	-.004 (.013)	.030 (.014)**	.008 (.012)	-.017 (.013)
nosingle	-.368 (.232)	-.520 (.247)**	.037 (.214)	-.256 (.229)
edu_gap	-.017 (.012)	.029 (.014)**	-.000 (.012)	-.003 (.012)
activelabor	-.033 (.035)	.112 (.038)***	.029 (.033)	.040 (.035)
mexperience	-.026 (.010)***	.016 (.010)	-.010 (.009)	.060 (.011)***
lexperience	.011 (.007)	-.003 (.008)	-.004 (.007)	.026 (.008)***
farmgroup	-.057 (.090)	-.093 (.107)	.089 (.087)	.186 (.098)*
credass	.053 (.067)	.090 (.076)	.120 (.064)*	.004 (.069)
SIMLESA	.282 (.084)***	-.217 (.102)**	.093 (.083)	.071 (.089)
total_land	-.031 (.013)**	-.077 (.016)***	-.051 (.010)***	-.005 (.010)
fertavail	.033 (.065)	.158 (.074)**	.027 (.063)	-.038 (.067)
drought	.113 (.065)*	.126 (.074)*	.041 (.062)	.131 (.067)**
pest	.021 (.077)	-.061 (.088)	-.154 (.074)**	.072 (.081)
crpdam_lst	.065 (.089)	.245 (.096)**	-.039 (.086)	.082 (.094)
Plot characteristics				
plotsize	.063 (.037)*	.154 (.049)***	.289 (.031)***	.000 (.033)
plotdistance	.002 (.001)**	-.006 (.002)***	-.001 (.001)	.001 (.001)
tenure	.134 (.106)	.695 (.156)***	.328 (.100)***	.023 (.107)
pm_male	-.051 (.077)	.074 (.088)	.113 (.073)	-.069 (.078)
pm_female	.044 (.096)	.208 (.109)*	.050 (.093)	.016 (.100)
slope	-.003 (.070)	.170 (.080)**	-.013 (.066)	.006 (.071)
fertility	.064 (.072)	-.006 (.080)	.053 (.068)	.130 (.072)*
depth	.069 (.074)	-.009 (.083)	.025 (.070)	.086 (.074)
District dummies				
Lilongwe	.547 (.116)***	-.115 (.117)	-.386 (.105)***	-.047 (.114)
Mchinji	.641 (.145)***	-.298 (.158)*	-.370 (.136)***	.003 (.149)
Kasungu	.377 (.133)***	-.359 (.144)**	-.431 (.120)***	-.103 (.130)
Salima	-.260 (.167)	-.006 (.157)	-.105 (.140)	-.169 (.149)
Ntcheu	.638 (.133)***	-.182 (.139)	-.022 (.125)	-.252 (.133)*
Constant	-1.086 (.262)***	-1.884 (.312)***	-.170 (.253)	.628 (.269)**
Regression diagnostics of MVP model				
Number of observations	1847			
Log likelihood	-7778.5767			
Wald chi2 (232)	1053.75***			

***p<0.01, **p<0.5, *p<0.1

Table 5
Marginal effects of multivariate probit model

Explanatory variables	Dependent variables			
	Legume intercropping (LI)	Residue cover (RC)	Soil and stone bunds (SSB)	Box ridges (BR)
Socioeconomic characteristics				
gender_head	.070	-.002	.154**	.241***
age_head	-.0004	.001	-.0003	-.00002
edu_head	-.0004	-.005	-.001	.001
nosingle	-.095	.011	-.198**	-.250***
edu_gap	-.001	.0002	.012***	.007
activelabor	.034***	-.011	.033***	-.010
mexperience	-.003	-.004	-.009***	.004
lexperience	.002	.005**	.010***	-.001
farmgroup	.002	.117***	.037	.037
credass	.048***	.074***	-.003	.024
SIMLESA	.044*	.003	.058	.014
total_land	-.017***	-.022***	.003	.003
fertavail	.012	-.063***	.185***	.056**
drought	-.007	.040**	.036	-.013
pest	.058***	.147***	-.096***	-.087***
crpdam_lst	.027	-.099***	-.055*	.005
Plot characteristics				
plotsize	.068***	-.0003	-.011	-.001
plotdistance	-.0003	.0002	-.001**	-.001
tenure	-.010	.069**	.126***	.083**
pm_male	.020	.014	.044	.001
pm_female	.045*	-.005	.050	-.105***
slope	-.028	-.002	-.050**	.003
fertility	-.001	-.037*	-.069***	-.115***
depth	.007	.063***	.051**	.024
District dummies				
Lilongwe	-.104***	.118***	.027	.034
Mchinji	-.137***	.079*	-.078*	-.015
Kasungu	-.110***	.057	-.012	.058*
Salima	-.161***	-.001**	-.067	-.093**
Ntcheu	.016	.089	-.024	.109

Explanatory variables	Dependent variables			
	Crop rotation (CR)	Manure	Chemical fertilizer (CF)	Improved variety (IV)
Socioeconomic characteristics				
gender_head	.100	.108**	.022	.077
age_head	-.00003	-.001	-.001	-.003***
edu_head	-.001	.007**	.003	-.004
nosingle	-.135	-.148**	.015	-.076
edu_gap	-.006	.007**	-.0001	-.001
activelabor	-.011	.028***	.011	.012
mexperience	-.009***	.004	-.004	.019***
lexperience	.004	-.001	-.002	.008***

farmgroup	-.020	-.022	.035	.056*
credass	.018	.022	.048*	.001
SIMLESA	.102***	-.049**	.037	.022
total_land	-.011**	-.018***	-.020***	-.002
fertavail	.011	.038**	.011	-.012
drought	.039*	.030*	.016	.042**
pest	.007	-.014	-.061**	.023
crpdam_lst	.023	.064**	-.015	.025
Plot characteristics				
plotsize	.022*	.040***	.112***	.0001
plotdistance	.001**	-.002***	-.001	.0003
tenure	.045	.123***	.130***	.007
pm_male	-.018	.018	.045	-.022
pm_female	.015	.052*	.020	.005
slope	-.001	.040**	-.005	.002
fertility	.022	-.001	.021	.042*
depth	.024	-.002	.010	.028
District dummies				
Lilongwe	.194***	-.027	-.153***	-.015
Mchinji	.243***	-.063*	-.146***	.001
Kasungu	.137***	-.077**	-.171***	-.034
Salima	-.084	-.001	-.042	-.056*
Ntcheu	.240***	-.041	-.009	-.085

***p<0.01, **p<0.5, *p<0.1; for model summary statistics see table 4

4. Conclusion

Understanding factors that influence adoption of conservation agricultural technologies is important in order to understand what works and what does not. This study used plot level data to identify factors that influence farmers' adoption of technologies. A multivariate probit regression model was used to further assess whether the CA technologies were mutually independent from each other. Of note, the likelihood ratio test of the independence of the equations was 347.33 and was statistically significant at one percent critical value. Therefore, it was concluded that the equations were interdependent. Furthermore, it was found that implementing some of the technologies resulted in some tradeoffs indicating that the technologies were substitutes while others indicated some positive relationships indicating complementarities. Results indicate that factors that affect adoption vary across technologies. In general, socioeconomic factors, plot level factors and location factors influenced adoption. Results indicate that policy targeting adoption of technologies should not treat them as standalone components but as packages that may have possible tradeoffs and complementarities.

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5. References

Amare, M., Asfaw, S., & Shiferaw, B. (2012). Welfare impacts of maize – pigeonpea intensification in Tanzania. *Agricultural Economics*, 1–17. doi:10.1111/j.1574-0862.2011.00563.x

Arslan, A., Mccarthy, N., Lipper, L., Asfaw, S., & Cattaneo, A. (2013). Adoption and intensity of adoption of conservation farming practices in Zambia. *"Agriculture, Ecosystems and Environment."* doi:10.1016/j.agee.2013.08.017

Cappellari, L., & Jenkins, S. (2003). The Stata Journal. *The Stata Journal*, *3*(3), 278–294.

Chirwa, E. W. (2005). Adoption of fertiliser and hybrid seeds by smallholder maize farmers in southern Malawi. *Development Southern Africa*, *22*(1), 1–13.

Feder, G., Just, E. R., & Zilberman, D. (2013). Adoption of Agricultural Innovations in Developing Countries : A Survey. *Economic Development and Cultural Change*, *33*(2), 255–298.

Giller, K. E., Witter, E., Corbeels, M., & Tittonell, P. (2009). Field Crops Research Conservation agriculture and smallholder farming in Africa : The heretics ' view. *Field Crops Research*, *114*, 23–34. doi:10.1016/j.fcr.2009.06.017

Government of Malawi. (2015). Malawi Agricultural Sector Wide Approach. Lilongwe: Government of Malawi.

Handschuch, C., & Wollni, M. (2013). ' Poverty , Equity and Growth in Developing and Transition Countries : Statistical Methods and. Goettingen: Gerg-August-Universitat Gottingen.

Kassie, M., Jaleta, M., Shiferaw, B., Mmbando, F., & Mekuria, M. (2013). Technological Forecasting & Social Change Adoption of interrelated sustainable agricultural practices in smallholder systems : Evidence from rural Tanzania. *Technological Forecasting & Social Change*, *80*(3), 525–540. doi:10.1016/j.techfore.2012.08.007

Kassie, M., Zikhali, P., Manjur, K., & Edwards, S. (2009). Adoption of sustainable agriculture practices : Evidence from a semi-arid region of Ethiopia. *Natural Resources Forum*, *33*, 189–198.

Knowler, D., & Bradshaw, B. (2007). Farmers ' adoption of conservation agriculture : A review and synthesis of recent research. *Food Policy*, *32*, 25–48. doi:10.1016/j.foodpol.2006.01.003

Marenya, P. P., & Barrett, C. B. (2007). Household-level determinants of adoption of improved natural resources management practices among smallholder farmers in western Kenya, *32*, 515–536. doi:10.1016/j.foodpol.2006.10.002

Ricker-Gilbert, J., & Jayne, T. S. (2010). What are the Dynamic Effects of Fertilizer Subsidies on Household Well-being ? Evidence from Malawi.

Teklewold, H., Kassie, M., & Shiferaw, B. (2013). Adoption of Multiple Sustainable Agricultural Practices in Rural Ethiopia. *Journal of Agricultural Economics*, *64*(3), 597–623. doi:10.1111/1477-9552.12011

Yu, L., & Hurley, T. M. (2007). Testing for Complementarity and Substitutability among Multiple Technologies : The Case of U . S . Hog Farms. In *American Agricultural Economics Association* (pp. 1–30).

ANNEX A

Table 3
Marginal effects for univariate probit regression on technologies (standard errors in parentheses)

	IC	**CR**	**RC**	**SSB**	**BR**	**manure**	**CF**	**IV**
IC	1	0.21	0.10	0.07	0.01	0.07	0.27	0.15
		(0.029)***	(0.025)***	(0.029)**	(0.032)	(0.023)***	(0.034)***	(0.031)***
CR	0.12	1	0.03	0.06	0.09	-0.07	-0.06	-0.001
	(0.017)***		(0.021)	(0.024)**	(0.025)***	(0.020)***	(0.027)**	(0.023)
RC	0.07	0.04	1	0.16	0.01	-0.002	-0.09	0.05
	(0.019)***	(0.026)		(0.025)***	(0.028)	(0.022)	(0.029)***	(0.026)*
SSB	0.04	0.06	0.13	1	0.01	0.07	0.04	0.04
	(0.018)**	(0.024)**	(0.020)***		(0.026)	(0.019)***	(0.027)	(0.023)*
BR	0.004	0.08	0.01	0.004	1	0.02	0.06	-0.01
	(0.017)	(0.022)***	(0.020)	(0.022)		(0.018)	(0.024)**	(0.021)
manure	0.05	-0.10	-0.004	0.10	0.03	1	0.27	0.03
	(0.021)**	(0.030)***	(0.026)	(0.028)***	(0.031)		(0.033)***	(0.028)
CF	0.14	-0.05	-0.06	0.03	0.06	0.15	1	0.01
	(0.017)***	(0.023)**	(0.020)***	(0.023)	(0.024)**	(0.018)***		(0.021)
IV	0.10	-0.003	0.04	0.04	-0.01	0.02	0.01	1
	(0.021)***	(0.025)	(0.023)*	(0.025)*	(0.026)	(0.020)	(0.027)	

N=1847, ***p<0.01, **p<0.05, *p<0.1