Adaption to Climate Change and Food Security: Micro-evidence from Malawi

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Abstract

This paper assesses factors governing farmers' decision to adopt adaptation/risk-mitigating strategies and evaluates the impact of adoption on crop productivity by utilizing household level data collected in 2011 from a nationally representative sample of 7842 households (11208 plots) in Malawi. We employ a multivariate probit (MVP) technique to model simultaneous and interdependent adoption decisions and utilize instrumental variable method for the impact estimates. The MVP results suggest that the decisions to adopt each of the farm management practices are quite distinct and to a larger extent the factors driving the adoption decisions are also different which entail the unsuitability of aggregating them into one adaptation variable. We find that favourable rainfall outcome affect positively the decisions to adopt short-term inputs such as improved seed and inorganic fertilizer whereas unfavourable rainfall outcome encourages farmer to adopt planting trees, maize-legume intercropping, use of organic fertilizer and soil and water conservation measures (SWC). Land tenure security increase the likelihood that farmer adopt strategies that will capture the returns from their investments in the long run and reduces the demand for short-term inputs. Access to extension advice, social capital and collective action also affect positively the adoption decisions suggesting the importance of information and networks. The impact estimate show that adoption of farm management practices has a positive and statistically significant impact on maize productivity suggesting the positive synergies between adaptation strategies and food security.

JEL Classification: Q01, Q12, Q16, Q18

Key words: Climate change, adaptation, impact, multivariate probit, instrumental variable, Malawi

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1. Introduction

Malawi is ranked as one of the world's twelve most vulnerable countries to the adverse effects of climate change (World Bank 2010). Droughts and floods, the most severe of these hazards, have increased in frequency, intensity, and magnitude over the past twenty years, with dire consequences on food and water security, water quality, energy resources, and sustainable livelihoods of the most rural communities. The adverse effects of climate change and variability in Malawi are skewed disproportionately towards agriculture. Malawian subsistence farmers suffer from climate related stressors in different ways through droughts, dry spells and floods, erratic and unreliable rainfalls (Chinsinga, 2012). Using data from the 2005 Integrated Household Survey (IHS2), Makoka (2008) has clearly underscored Malawi's vulnerability to the adverse effects of climate change in the agricultural sector. Given that agricultural production remains the main source of income for most rural communities, adaptation of the agricultural sector to the adverse effects of climate change will be imperative to protect and improve the livelihoods of the poor and to ensure food security (Bradshaw et al., 2004; Wang et al., 2009). Studies using data for India show that adaptation can reduce the damage to agriculture by about 10 – 20% (Jacoby et al., 2010).

Adaptation to current or expected climate variability and changing average climate conditions, involves both disaster risk management focusing on preventing, mitigating and preparing to deal with shocks and adaptive change management that aim to modify behaviours and practices over the medium- to long-term. Adaptation activities can reduce the impacts of climate change and buffer their effects, reducing the negative impacts on humans and the environment. At micro (farmer) level adaptation strategies encompass a wide range of activities including climate-smart agricultural options. Examples include modifying planting times and changing to varieties resistant to heat and drought (Phiri and Saka, 2008); development and adoption of new cultivars (Eckhardt et al., 2009); changing the farm portfolio of crops and livestock (Howden et al., 2007); improved soil and water management including conservation agriculture (Kurukulasuriya and Rosenthal, 2003; McCarthy et al., 2011); integrating the use of climate forecasts into cropping decisions (Howden et al., 2007); increased use of fertilizer and irrigation (Howdenet al., 2007); increasing regional farm diversity (Reidsma and Ewert, 2008); and shifting to non-farm livelihoods (Morton, 2007).

It is important to note that farmers are more likely to adopt a mix of measures to deal with a multitude of agricultural production constraints than adopting a single practice. Past studies assessed the specific technology adoption decision (fertilizer or SWC structures), which fails to account for complementarities and/or substitutabilities among different practices. Some recent empirical studies of technology adoption decisions assume that farmers consider a set (or bundle) of possible technologies and choose the particular technology bundle that maximizes expected utility (Teklewold et al., 2013). Thus, the adoption decision is inherently multivariate and attempting univariate modelling excludes useful economic information contained in interdependent and simultaneous adoption decisions. To address this challenge we employ a multivariate probit (MVP) technique to model simultaneous and interdependent adoption decisions by farm households. We do so by using a nationally representative plot-level data with rich socio-economic information merged with climatic information. We make particular effort in trying to use geo-referenced information in our analysis to unearth the role of bio-physical and climatic factors in governing farmers' adoption decisions of adaptation/ risk-mitigating strategies. We also try to estimate the causal impact of adoption of these practices on maize productivity[2].

The rest of the paper is organized as follows. Data source, sample composition and descriptive results are presented in section two. The third section presents the conceptual framework and analytical methods with emphasis on empirical models and hypothesized relationships. The main analytical results are presented and discussed in section four. Section five concludes by presenting the key findings and the policy implications.

2. Data and descriptive analysis

2.1 Data description

The Third Integrated Household Survey (IHS3) was conducted from March 2010 to March 2011 covering a period of twelve months. The Survey is a nationally representative sample survey designed to provide information on the various aspects of household welfare in Malawi. The survey collected information from a nationally representative sample of 12,288 households statistically designed to be representative at both national, district, urban and rural level hence the survey provides reliable estimates for these levels (IHS, 2012). The full sample consists of about 16,372 plots, however in this study we focused on plots that have been cultivated with maize during the survey rainy season (11,208 plots) given the fact that maize is a staple crop which is produced and consumed by large proportion of rural Malawian. As discussed earlier maize production is critically important to the Malawian economy and to the livelihoods of most Malawian people. Detail about the sampling procedures can be found from the report produced by the Centre of Statistical Authorities (CSA) in Malawi (IHS, 2012)

All sample households were administered the multi-topic Household Questionnaire that collected household composition and characteristics, health, wage employment, anthropometrics and income sources, as well as data on consumption, food security, nonfarm enterprises, and durable and agricultural asset ownership, among other topics. The sample households that were involved in agricultural activities (through ownership and/or cultivation of land, and/or ownership of livestock) were administered the Agriculture Questionnaire module. The Agriculture Questionnaire asked for information on land tenure, labour and non-labour input use, and crop cultivation and production at the plot level. Location and land area of the plots are also recorded using handheld global positioning system (GPS) devices which then created a possibility of linking household level data with geographic information system (GIS) databases (IHS, 2012). In additions to household level questionnaire, the survey also administered a community level survey instrument that captures issues related to collective action, access to information, access to market and access to road among others.

We merge IHS3 data with historical data on rainfall estimates (RFE) at the household level to control for the effects of the variation in rainfall on farmers' adoption decisions. Malawi IHS3 survey data included georeferenced household and plot level Latitude and Longitude coordinates which allowed us to extract the remote sensing time series indicators such as RFE cumulative sum. RFE data are obtained from the National Oceanic and Atmospheric Administration's Climate Prediction Centre (NOAA-CPC) for the period of

[2] We focus primarily on stable crop – maize– which is predominantly grown by farmers in the study region.

1996-2011. RFE data we use are based on the latest estimation techniques for 10-day intervals and have a resolution of 8 km[3].

Taking the annual measure of main cropping season rainfall at each enumeration area, we calculate the coefficient of variation for rainfall (CV), measured as the standard deviation divided by the mean for the respective periods: 1996-2011. One of the major advantages of the CV is that it is scale invariant, providing a comparable measure of variation for households that may have very different income levels. We argue that the climate variability, represented by the CV, is a major determinant of household behaviour in rural areas as a result of the dependence on agriculture for subsistence consumption and livelihoods. This is distinct from the literature which examines the effects of weather shocks using the level of rainfall or deviation from its mean. Whilst weather shocks are clearly important, we give particular attention to climate variability, as a proxy for expectations about future uncertainty.

Agro-ecological and production capacity suitability index is also obtained from the Global Agro-ecological Zones (GAEZ) database and merged to the household dataset to control for the effects of bio-physical characteristics. Adequate agricultural exploitation of the climatic potentials and maintenance of land productivity largely depend on soil fertility and the management of soils on an ecologically sustained basis. The agro-ecological suitability and productive capacity suitability index are presented for three input levels (high, intermediate and low) at crop level[4]. We also merged the IHS3 EA with the Malawi 2009 election results to control for the effects of voting pattern on household participation in the Malawi farm input subsidy programme (FISP). Democratic Progressive Party (DPP) was the ruling party at the time and the main opposition party was the Malawi Congress Party (MCP). The variables created include vote counts in the constituencies that cover the IHS3 EAs, DPP votes as a share of total votes cast and the MPP votes as a share of total votes.

2.2. Variables and descriptive statistics

We focus in this paper on six different farm management measures (maize-legume intercropping, soil and water conservation, tree planting, use of organic fertilizer, improved maize varieties and use of inorganic fertilizers)[5] that are considered to help reduce exposure to climate shocks and at the same time also help as adaptation strategies. Table 1 show the proportion of households that implemented different farm management practices on their plots disaggregated by province.

Use of planting perennials trees is part of a sustainable agricultural system in Malawi. Selected tree and shrub species are often planted either sequentially (during fallow) or contemporaneously (intercropped) with an annual food crop. Doing so helps maintain soil cover, improve nutrient levels, increase soil organic matter (via the provision of mulch), improve water filtration, improve soil loss due to erosion and flooding, provides shades for other crops and provides a secondary source of food, fodder, fibre and fuel (Garrity et al., 2010; Ajayi et al., 2009; McCarthy et al., 2011; Mercer, 2004; Franzel and Scherr, 2002).

[3] See http://www.cpc.ncep.noaa.gov/products/fews/RFE2.0_desc.shtml for more information on RFE algorithms.

[4] See http://www.fao.org/nr/gaez/about-data-portal/agricultural-suitability-and-potential-yields/it/ for more information on suitability indices.

[5] We lack data on conservation agriculture practices and as result those are not included in our analysis.

Planting trees also increases carbon sequestered both above and below ground, thereby contributing to GHG mitigation (Verchot et al., 2007). Thus farm management practices like tree planting can help reduce exposure to climate shocks and at the same time also help as adaptation strategies. In our case, tree planting is used on 39% of maize plots. The proportion is the lowest in the Central Province.

The maize–legume intercropping system is one option for sustainable intensification that can help farmers to increase crop productivity through nitrogen fixation and also helps to maintain productivity in a changing climate (Delgado et al., 2011). Maize–legume intercropping is practiced on about 22.1% of the plots during the cropping season used for this analysis, especially prevalent in the Southern Province (35.5%).

There are a number of fixed investments in structures for SWC, in addition to some of tree planting investments discussed above. For the farmer, these structures can provide benefits by reducing water erosion, improving water quality, and promoting the formation of natural terraces over time, all of which should lead to higher and less variable yields. Such structures also often provide benefits to neighbors and downstream water users by mitigating flooding, enhancing biodiversity, and reducing sedimentation of waterways (Blanco and Lal 2008; McCarthy et al., 2011). Structures include contour bunds – built of either earth or stone, terraces, gabions/sandbags, vetiver grass, tree belts or drainage ditches. Our data shows that about 45% of the maize plots have been treated with SWC structures and this figure is highest in the Central Province (47%) followed by the Sothern Province (46%). As with planting trees, SWC structures often entail large up-front costs, with benefits accruing – sometimes slowly – over time (McCarthy et al., 2011).

Use of organic fertilizer is another major component of a sustainable agricultural system and a commonly suggested method of improving soil fertility in crop-livestock systems. The benefits of the use of organic fertilizer in crop production are improvements in soil physical properties and the provision of N, P, K, and other mineral nutrients. The application of organic fertilizer increases soil organic matter content, and this leads to improved water infiltration and water holding capacity as well as an increased soil carbon content (Kassie et al., 2008; Marenya and Barrett, 2007). Our data shows that organic fertilizer is used on about 12.2% of the sample maize plots. The adoption seems to be larger in the Central Province (16.8%) compared to the other two provinces.

The use of high yielding varieties is another practice that could improve food security and income for the rural population by improving productivity (e.g., Kijima et al., 2008; Mendola, 2007; Berceril and Abdulai, 2010; Asfaw et al., 2012b, 2012c; Amare et al., 2011 etc). Nevertheless it is an empirical question whether it is superior to the local varieties in harsh climatic conditions. The plot planted with improved maize varieties is about 50.7% and this figure is larger in the Northern Province (55.4%).

The average inorganic fertilizer used for maize in the study areas is about 63 kg⁄acre. About 74.8% maize sample plots are treated with inorganic fertilizer which is relatively high compared to other SSA countries which is largely attributed to the farm input subsidy program. Looking across the different provinces, there seems to be no significant differences. In all the three provinces, the proportion of plots treated with inorganic fertilizer is over 70%. Although the productivity impact of using inorganic fertilizer is widely documented, it is important to note that along with other inputs, may cause soil degradation in the long term due to the depletion of organic matter in the topsoil (Branca et al., 2011; FAO, 2011; Tilman et al., 2002).

< TABLE 1 ABOUT HERE>

Table 2 presents productivity of maize by adoption status and also disaggregated by province. The sources of the observed yield effect of the adoption of these technologies are expected to result in better food security status for the households. The descriptive statistics show a productivity difference in maize yield between adopters and non-adopters. For instance adopters of inorganic fertilizer have about 80.5% more productivity compared to the non-adopters while adopters of maize-legume intercropping have about 62.7% more. The lowest change in maize productivity is reported for tree planting, which is about 8.7%. Overall the unconditional summary statistics in table 2 suggest that adoption of any of the farm management practices may have a role in affecting quantity of maize produced per unit of land. The significant difference between the adopter groups also remains subjectively the same when we look at disaggregated analysis by province. However, because adoption is endogenous, a simple comparison of the outcome indicators of adopter and non-adopters has no causal interpretation. Therefore, in the subsequent part of the chapter, a rigorous analytical model is estimated to verify whether these differences in mean productivity of maize remain unchanged after controlling for all confounding factors. To measure the impact of adoption, it is necessary to take into account the fact that households who adopted the practices might have achieved a higher productivity even if they had not adopted.

< TABLE 2 ABOUT HERE>

Summary statistics of explanatory variables disaggregated at provincial level are presented in table 3. The variables hypothesized to explain adoption decision and productivity are identified from past empirical work, economic theory and in some case based on intuition. Adoption decisions of the farmer for specific farm management practice are assumed to be derived from the maximization of a discounted expected utility of farm profit subjected to imperfect or missing factor markets for land, labour, credit and perception of farm households (D'Souza et al., 1993; Neill and Lee, 2001; Isham, 2002; Arellanes and Lee, 2003; Gebremedhin and Scott, 2003; Lee, 2005; Marenya and Barrett, 2007; Knowler and Bradshaw, 2007; Kassie et al., 2008, 2010; Asfaw et al., 2012b, 2012c; Wollni et al., 2010). Variables hypothesized to explain adoption decision and productivity are summarized under five categories, (1) household socio-demographic, (2) household wealth indicators[6], (3) plot level characteristics, (4) climatic and bio-physical indicators and (5) institutions and transaction cost indicators.

< TABLE 3 ABOUT HERE>

[6] The household wealth index is constructed using principal component analysis and takes into account the number of rooms in the dwelling, a set of dummy variables accounting for the ownership of dwelling, mortar, bed, table, chair, fan, radio, tape/CD player, TV/VCR, sewing machine, paraffin/ kerosene/ electric/ gas stove, refrigerator, bicycle, car/motorcycle/minibus/lorry, beer brewing drum, sofa, coffee table, cupboard, lantern, clock, iron, computer, fixed phone line, cell phone, satellite dish, air-conditioner, washing machine, generator, solar panel, desk, and a vector of dummy variables capturing access to improved outer walls, roof, floor, toilet, and water source. The household agricultural implement access index is also computed using principal components analysis and covers a range of dummy variables on the ownership of hand hoe, slasher, axe, sprayer, panga knife, sickle, treadle pump, watering can, ox cart, ox plough, tractor, tractor plough, ridger, cultivator, generator, motorized pump, grain mail, chicken house, livestock kraal, poultry kraal, storage house, granary, barn, and pig sty.

3. Empirical strategies

3.1 Adoption decision –Multivariate probit model

Foster and Rosenzweig (2010) and de Janvry et al. (2010) point out that the adoption and input uses are the outcomes of optimizing by heterogeneous agents. 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. Viewing adoption through the lens of optimization by rational agents, households adopt a given farm management practice if only if adoption is actually a choice that can be taken and at the same time adoption is expected to be profitable or otherwise advantageous (de Janvry et al., 2010). Following de Janvry et al. (2010), Becerril and Abdulai (2010), Asfaw et al. (2012a, 2012b 2012c), Amare et al. (2011) and Teklewold et al. (2013) the adoption decision can be modelled in a random utility framework. The difference between the utility from adoption (U_{Ai}) and non-adoption (U_{Ni}) of these measures may be denoted as G^*, such that a utility-maximizing farm household, i, will choose to adopt, if the utility gained from adopting is greater than the utility of not adopting $(G^* = U_{Ai} - U_{Ni} > 0)$.

However farmers are more likely to adopt a mix of measures to deal with a multitude of agricultural production constraints than adopting a single practice. Past studies assessed the specific technology adoption decision (e.g. fertilizer or SWC structures), which fails to account for complementarities and/or substitutabilities among different practices. The choice of measures adopted more recently by farmers may be partly dependent on earlier technology choices. Some recent empirical studies of technology adoption decisions assume that farmers consider a set (or bundle) of possible technologies and choose the particular technology bundle that maximizes expected utility. Thus, the adoption decision is inherently multivariate and attempting univariate modelling excludes useful economic information contained in interdependent and simultaneous adoption decisions (Dorfman, 1996; Teklewold et al., 2013).

Thus we employ a multivariate probit (MVP) technique to model simultaneous and interdependent adoption decisions by farm households. We use multiple maize plot observations to jointly analyze the factors that facilitate or impede the probability of adopting of these practices in smallholder maize system. This approach recognizes the likely correlations between the adoption decisions across the different practices for the same farm household through unobserved characteristics. It simultaneously models the influence of the set of explanatory variables on each of the different practices, while allowing the unobserved and unmeasured factors (error terms) to be freely correlated. One source of correlation may be complementarities (positive correlation) and substitutabilities (negative correlation) between different practices.

The multivariate probit econometric model is characterized by a set of binary dependent variables (G_{ij}) that equals 1 if a farmer adopt the practice and zero otherwise, such that

$$G_{ij}^{*} = \beta X_{ij} + u_{ij} \text{ with } G_{ij} = \begin{cases} 1 & if G_{ij}* > 0 \\ 0 & otherwise \end{cases} \quad (1)$$

Where $j = 1,..m$ denotes the technology choices available. In equation (1) the assumption is that a rational i^{th} farmer has a latent variable, G_{ij}^{*}, which captures the unobserved preferences or demand associated with the j^{th} choice of the practices. This latent variable is assumed to be a linear combination of observed characteristics (X_{ij}), household, plot, climatic and community characteristics that affect the adoption of the j^{th} practice, as well as unobserved characteristics captured by the error term u_{ij}.

If adoption of a particular practice is independent of whether or not a farmer adopts another practice (i.e., if the error terms, are independent identically distributed (iid) with a standard normal distribution), then equation (1) specify univariate probit models, where information on farmers' adoption of one farming practice does not alter the prediction of the probability that they will adopt another practice. However, if adoption of several farming practices is possible, a more realistic specification is to assume that the error terms in equation (1) jointly follow a multivariate normal (MVN) distribution, with zero conditional mean and variance normalized to unity.

3.2 Instrumental variable (IV) method

In this model, the observed indicator variable, G_i, indicates the presence or absence of treatment, which in this case refers to adoption of farm practices by household i^{th} as defined above. Formally, given the unobserved or latent variable, G_i^{*} , and its observed counterpart, G_i (dummy for adoption of practices), the treatment-effect equation can be expressed as:

$$G_{ij}^{*} = \beta X_{ij} + u_{ij} \text{ with } G_{ij} = \begin{cases} 1 & if G_{ij}* > 0 \\ 0 & otherwise \end{cases} \quad (2)$$

$$Y_{ij} = \alpha V_{ij} + \gamma G_{ij} + e_{ij} \quad (3)$$

where Y_{ij} represent outcome variables (maize yield per acre), V_{ij} is a vector of exogenous variables thought to affect maize productivity, e_i is random disturbances associated with the impact model. The impact of adoption on the outcome variable is measured by the estimates of the parameter γ in a two-stage simultaneous procedure. Note that it is not possible to simply estimate Equation (3) because the decision to adopt may be determined by unobservable variables that may also affect maize productivity. If this is the case, the error terms in Equations (2) and (3) are correlated, leading to biased estimates of γ, which is the productivity effect of adopting those practices. The decision to adopt or not is not voluntary and may be based on individual self-selection. Farmers who adopted may have systematically different characteristics from the farmers who did not adopt, and they may have decided to adopt based on expected benefits. Unobservable characteristics of farmers and their farms may affect both the adoption decision and the maize yield, resulting in inconsistent estimates of the effect of adoption on productivity. The solution is to explicitly account for such endogeneity using an instrumental regression technique that assumes a joint normal error distribution (Di Falco et al., 2011).

The choice of instruments is challenging as we need a variable that is correlated with the adoption of farm management practices, but not with the error term of the yield models. We considered using coefficient of variation of rainfall (1996-2011) as potential instruments for household decision to adopt adaptation measures during the current year. Whilst the level of rainfall or rainfall shocks tend to be used as instrumental variables or proxy variables for income or covariate income shocks, there are limitations to this (Rosenzweig and Wolpin, 2000). As a result, there are identification issues with using the level of rainfall or rainfall shocks. For example, more rainfall is usually defined as good, i.e. the coefficient is positive. However, even controlling for a quadratic rainfall term – expected to have a negative coefficient, indicating diminishing returns to rainfall – may not be sufficient identification. If farmers form expectations about the climatic conditions of their area, we might expect that they plant crops and use farm practices that are suited to that area. Any deviation from this optimal cropping decision in terms of more or less rainfall may not be welfare improving. The formation of these expectations is key for production. Thus for households in rural areas, rainfall variation across space and time should generate corresponding variation in household response or behaviour in term of change in farm practices that will in turn create variation in agricultural output and thus household income. For this reason, we focus on rainfall variability which, we argue, generates uncertainty about expected climatic conditions. However, it is important to control for recent rainfall shocks as this is likely to be correlated with the CV which we did in our estimation.

We also constructed a variable that capture the share of households in the community that received extension advice on specific farm management practices and use it as an additional instrument in our estimation. Given that this variable is measured at community level, such indicator is unlikely to be directly correlated with the maize yield although may be correlated with the propensity to adopt farm practices. We are quick to point out that selected instrumental variables may not be perfect, but we will try to demonstrate that the test statistics support the idea that they help to bolster our case. We assess the quality of our instruments by using an F-test of the joint significance of the excluded instruments[7]. According to Stock and Staiger (1997), the weak instrument hypothesis will be rejected if an F-test is greater than 10. Additionally, as part of a robustness check, we also perform over identification tests of the model.

[7] As discussed above an instrumental variable must not be correlated with the equation's disturbance process and it must be highly correlated with the included endogenous regressor. We may test the latter condition by examining the fit of the first-stage regression. The first-stage regression is a reduced-form regression of the endogenous regressor, G_i, on the full set of instruments, Y_i. The relevant test statistics here relate to the explanatory power of the excluded instruments, Y_i, in this regression. A statistic commonly used as recommended by Bound et al. (1995), is the R^2 of the firs-stage regression with the included instruments partialled out. The test may be expressed as the F-test of the joint significance of the Y_i instruments in the first-stage regression.

4. Regression results

4.1. Adoption decision – MVP results

The maximum likelihood estimates of the MVP model of adoption of farm management practices are presented in Table 5. It provides the driving forces behind farmers' decisions to adopt farm management strategies where the dependent variable takes the value of 1 if the farmer adopts specific practices and 0 otherwise. The model fits the data reasonably well – the Wald test of the hypothesis that all regression coefficients in each equation are jointly equal to zero is rejected $(\chi^2(182) = 6440, P = 0.00)$. Also the likelihood ratio test $(\chi^2(15) = 2367, P = 0.00)$ of the null hypothesis that the covariance of the error terms across equations is not correlated is also rejected as reported in Table 4. We also find that the estimated correlation coefficients are statistically significantly different from zero in eleven of the sixteen pair cases, where two coefficients are negative and the remaining nine are positive, suggesting the propensity of adopting a practice is conditioned by whether a practice in the subset has been adopted or not. Besides justifying the use of MVP in comparison to the restrictive single equation approach, the sign of the coefficients support the notion of interdependency between adoption decision of different farm management practices which may be attributed to complementarities or substitutability between the practices. We find that improved seed is complementary to use of inorganic fertilizer but substitutable with maize-legume intercropping. The correlation coefficient between two yield enhancing technologies (inorganic fertilizer and improved seed) is the highest among all (17%). On the other hand as expected inorganic fertilizer is significantly substitutable with the use of organic fertilizer, nevertheless it's complementary with maize-legume intercropping and SWC measure. Adoption of organic fertilizer is also significantly complementary with planting tree, maize-legume intercropping and SWC measure. The positive correlation between adoption of maize-legume intercropping and use of inorganic and organic fertilizer is not expected given the fact that legumes are supposed to help in fixing nitrogen contributing to improving the fertility of the soil. Planting tree is complementary with maize-legume intercropping and adoption of SWC measures and also maize-legume intercropping is complementary with adoption of SWC measure.

< Table 4 ABOUT HERE>

The MVP results reported in table 5 show that the adoption decisions of different farm management practices are quite distinct and to a larger extent the factors governing the adoption decision of each of them are also different. The results suggest the heterogeneity in adoption of farm management practices and accordingly, the unsuitability of aggregating them into one adaptation variable. Age of the household head is negatively and strongly correlated with the likelihood of adoption of improved seed and inorganic fertilizer while it's positively correlated with adoption of organic fertilizer, tree planting and maize-legume intercropping. The coefficient of age and age-square is statistically significant with opposite signs perhaps suggesting that younger household heads tend to adopt practices that are yield enhancing but relatively risky and capital intensive while the older ones engage more on traditional practices that are less risky and require less finance. We also find a differentiated role of gender on adoption decision. For instance the likelihood of adoption of improved seed is significantly higher for male compared to female headed households while the opposite is the case for adoption of organic fertilizer and maize-legume intercropping.

We also find a differentiated impact of education of the head and spouse on the adoption of different practices and that use of some practices may entail intensive knowledge whereas others not. Education of the household head takes a positive sign for the case of adoption of improved seed and inorganic fertilizer while takes negative sign for the maize–legume intercropping. Result of the correlation between education of the head and maize-legume intercropping is quit intriguing. On the one hand the coefficient of the variable that reflect whether the head can read/write Chichewa (the local language) is positive and significant but conversely the coefficient of the years of education of the head is negative and significant, perhaps suggesting that adoption of this practice require basic knowledge unlike others. Contrary to other findings (e.g. Teklewold et al., 2013), education status of the spouse does not seem to play a significant role in the adoption decision of farm management practices with the exception of organic fertilizer.

As expected, the household wealth proxies such as livestock holding, wealth index and agricultural implements index have also heterogeneous impact. Livestock holding is negatively and strongly related to the household decision to adopt inorganic fertilizer, perhaps suggesting some sort of substitution between the uses of fertilizer with manure given the fact that livestock waste is the most important source of manure for farmers in most rural areas. Nevertheless it is positively correlated to use of organic fertilizer, maize-legume intercropping and use of SWC measures. Wealth index takes a positive sign and significant in all the cases with the exception of maize-legume intercropping all suggesting the positive role of household wealth in the adoption decision. Contrary to the wealth index results agricultural implements index is negatively and strongly related to adoption improved seed and inorganic fertilizer while it's positively correlated with the rest of the practices. Overall these results could imply that the higher the capacity of the household to absorb risk and finance an investment in additional activities, the greater the likelihood of adopting some of these adoption of adaptation/ risk-mitigating strategies. Asset holding can also play a valuable indirect role in facilitating access to credit which is consistent with other findings (Kristjanson et al., 2005 and Teklewolde et al., 2013)

Farm size has a positive effect on adoption of improved seed and inorganic fertilizer although the coefficient is statistically significant only for the latter. However, it is negatively and strongly related with adoption of the rest of the practices. As expected, larger farms appear to use more modern inputs compared to smaller farms while households with smaller farm engage more on less capital intensive and traditional technologies which is not surprising. Again these results demonstrate the differential role of land holding in promoting adoption of these practices. Using irrigation on the plot seems to increase the propensity of adoption of inorganic and organic fertilizer and SWC measures. We also find that farm households with highly fertile soils are less likely to implement some of these farm management practices. The sign of the coefficients are all negative and statistically significant for four of the practices. Consistent with our expectation, results also show that the higher the extent of erosion on the plot, the less likely the farmer adopts inorganic fertilizer and the more likely they adopt planting tree and SWC measure.

The role of land tenure structure also seems very important. We find that farm households who own the land are less likely to adopt improved seed and inorganic fertilizer compared to farmers who rented the plot. On the other hand the decision to adopt organic fertilizer, planting tree and maize-legume intercropping is positively and strongly related to owning the land. Our results are consistent with a number of studies that have demonstrated that security of land ownership has substantial effect on the agricultural performance of farmers (e.g. Kassie and Holden, 2008; Deininger et al., 2009; Teklewold et al., 2013). Better tenure security increase the likelihood that farmer adopt strategies that will capture the returns from their investments in the long run. On the other hand farmers with less tenure security tend to demand more short-term inputs like inorganic fertilizer and improved seed. Kassie and Holden (2008) also found that in areas where land is scarce and search costs are high, farmers are likely to apply more short-term inputs on rented plots than owned plots. This finding is also consistent with the perspective that planting trees serve a double function: reducing exposure to weather shocks and enhancing tenure security by signalling ongoing use and investment (Deininger et al., 2009).

As expected, the results also suggest the importance of climatic variables in explaining the probability of farm households' decision to adopt adaptation/ risk-mitigating strategies. We find that variability in rainfall as represented by the coefficient of variation of rainfall variable is strongly associated with adoption of most of these practices although the effect is heterogeneous. For instance, adoption of inorganic fertilizer, organic fertilizer and SWC measures is negatively and significantly correlated with the coefficient of variation of precipitation. On the other hand the probability of adopting tree planting is high in areas where the rainfall variability is high as represented by the positive coefficient of the variable. Recent climatic variables also seem to play role in determining the probability of adoption of farm management practices. Precipitation in the last rainy season seems to affect positively the propensity to adopt improved seed and inorganic fertilizer in the current year though the coefficient for the latter one is insignificant. On the other hand the decision to adopt organic fertilizer, planting tree, maize-legume intercropping and SWC measures in the current cropping season is negatively correlated with the average precipitation of the last cropping season. We also find that farm households who experience a climatic shock (i.e. drought) in the past year are less likely to adopt improved seed, inorganic fertilizer and organic fertilizer in the current year while the opposite is the case for planting tree and SWC measures. These results suggest that favourable rainfall outcome affect positively the decisions to adopt short-term inputs such as improved seed types and inorganic fertilizer use whereas unfavourable rainfall outcome encourages farmer to adopt planting trees, maize-legume intercropping, use of organic fertilizer and SWC measures which in turn helps in conserving soil moisture, improve soil organic matter and reduce soil loss from erosion and flooding. This is consistent with the findings of Kassie et al. (2010) and Teklewold et al. (2013) who found that yield enhancing technologies like inorganic fertilizer provide a higher crop return in wetter areas than in drier areas.

Better access to services, apart from influencing availability of technology, has an effect on farmers' decision on the use of input and output markets, and the availability of information and support organizations, as well as the opportunity costs of labour. We find a differentiated effect of distance related variables. Farmers who are further away from daily market and major district centre are less likely to adopt strategies such as improved seed, inorganic fertilizer and SWC measures. Nevertheless the opposite seem to be the case for adoption of maize-legume intercropping. The further the farmers are away from the daily market and district centres, the more likely they adopt maize-legume intercropping, perhaps due to the fact that increased input costs increase the appeal of alternative inputs use, such as legume intercropping. As expected, maize price influences adoption decisions significantly though the sign of the coefficients are not uniform for all farm management practices. We find that adoption of improved seed, inorganic and organic fertilizer is positively and significantly associated with maize price, nevertheless the likelihood of adoption of planting trees and maize-legume intercropping seem to decreases with increase in maize price.

Results also show the key role of rural institutions and collective action in governing the adoption decisions of farm households. Access to government extension service increases significantly the likelihood of adoption of some practices. The higher the share of households who received extension advice on the specific practices in the community, the higher the probability of adoption with two exceptions – adoption of organic fertilizer and maize-legume intercropping. Good and timely information on new technologies and techniques is essential for farmers when deciding whether or not to adopt an innovation. Farmers who are frequently visited by extension agents tend to be more progressive and experiment with improved technique. The bottom line is that improving extension service both in terms of coverage and efficiency is essential in helping farmers to overcome barriers to information and adapt to climate change. This positive effect of farmer technology awareness variable is consistent with Shiferaw et al. (2008), Kristjanson et al. (2005), Kaliba et al. (2000), Di Falco et al. (2011) and Geberessiliese and Sanders (2006).

The coefficient of collective action index is negative and significant for inorganic fertilizer and planting tree whereas it's positive and significant for organic fertilizer and SWC measures. Our results are not that odd if we think that the public goods spillover impacts are greatest for SWC measures, followed by planting trees, legume intercropping, organic fertilizer, inorganic fertilizer and improved seeds respectively. The latter two having fairly limited spillovers with improved seeds as purely private, it's not surprising to see negative effect on inorganic fertilizer and no effect on improved seed, though we do think the results of tree planting is odd. We also find that the presence of village development committees in the community increase the likelihood of adoption of organic fertilizer, maize-legume intercropping and SWC measures, nevertheless it has negative and strong relation with adoption of inorganic fertilizer. We also find that the presence of credit and saving organizations in the community is positively and strongly associated with adoption of planting trees and maize-legume intercropping. With scarce information sources and high transaction costs, such informal institutions facilitate the exchange of information and enable farmers to access inputs on schedule and overcome credit constraints (Pender and Gebremedhin, 2007; Wollin et al., 2010).

As expected the estimated coefficients of receipt of fertilizer and improved maize coupons (participation in fertilize input subsidy program) are both positive and significant for the improved seed and inorganic fertilizer adoption equations, respectively. We expect that input coupon receipt is endogenous to the adoption decision, and hence, we need to instrument receipt of input subsidy. We do so using as instruments obtained from Malawi

2009 election results. We created a variable that capture the major party (DPP) votes as a share of total votes cast and use this as an instrument for household participation in the fertilizer input subsidy program. There is no reason to suspect the voting pattern in the community will affect the adoption decisions except through their effect on receipt of input coupon. We use the Rivers and Vuong (1988) approach to instrumentation and include the reduced form residuals from the instrumenting regression in the main adoption equation. The t-statistic of the predicted residual is only 0.01, which suggests that endogeneity is not a problem. As expected, we find that the participation in input subsidy program affect positively the probability of adoption of improved seed and inorganic fertilizer. Furthermore, adoption decision was found to vary across different agro-ecological zones. Regional dummies included in the models are found to be highly statistically significant for most of the practices (the point of reference is Northern Province).

< Table 5 ABOUT HERE>

4.2. Average productivity effect of adoption

Table 6 reports the estimates of OLS and instrumental variable (IV) regression model estimated with clustered standard errors at the household level. The first column presents the estimation by OLS of the maize productive function without controlling for any potential endogeneity problem and with a dummy variable equal to 1 if the farm household decided to adopt the farm management practices on their plot, 0 otherwise, with the exception of inorganic fertilizer which is a continuous variable. The second, third, fourth, fifth and sixth columns present, respectively, the estimated coefficients of IV regressions where we instrument for adoption of improved seeds (2), inorganic fertilizer (3), maize-legume intercropping (4), planting tree (5) and SWC measures (6). In this section we focus on the effect of each of the adaption strategies on quantity of maize produced per acre of land.

The simplest approach to investigate the effect of adoption of farm management practices on maize productivity consists of estimating an OLS model of productivity estimate that include dummy or continuous variables for adoption decision (Table 6, column (1)). This approach would lead us to conclude that there is difference in maize productivity by households that adopted the practices with respect to the productivity of households that did not adopt. As shown in Table 6, the coefficients of the adoption variables are all positive and statistically significant. This approach however assumes that adoption of these farm management practices is exogenously determined in the productive function while it is potentially endogenous variables. Therefore the estimation via OLS would yield biased and inconsistent estimates. The impact estimates presented further on uses an IV (treatment effect model when the adoption variable is dummy and 2SLS when the adoption variable is continuous) to account for this problem.

Before turning to the causal effects of adoption on maize productivity, we briefly discuss the quality of the selection instruments used. To probe the validity of our selection instruments we did run an auxiliary first stage regression where our adoption variable is regressed against the instruments and the other exogenous variables. In most of the cases we found that the excluded instruments are significantly correlated with the adoption variable. In some cases, for instance, the estimated coefficient of specific instrument (extension advice) is not significant in the adoption of SWC equation nevertheless both instrument (coefficient of variation of rainfall and extension advice) variables are jointly significant at 5%. The same is true for variables used to instrument adoption of improved seed and maize-legume intercropping (coefficient of variation of rainfall is not significant on its own but jointly significant with the other instruments). Overall with the exception of the SWC measure equation, over identification tests support the choice of the instruments, as do the F-test values for the first stage adoption equation. The F-statistic of joint significance of the excluded instruments is greater than 10, thus passing the test for weak instruments.

An interesting finding is that after controlling for all confounding factors, maize quantity produced per acre of land is significantly higher for female headed households compared to their male counter parts. The coefficient of gender is negative and significant in all specification with one exception. Female headed households tend to produce about 6-13% more of maize yield per acre of land compared to male household heads. Many studies show that productivity on plots managed by women are lower than those managed by men which are often attributed to difference in input use, such as improved seeds, fertilizers and tools, or other factors such as access to extension services and education (e.g., Quisumbing et al., 2001; Peterman et al., 2011). The estimated yield gaps ranged widely but many clustered around 20–30%, with an average of 25%. Our finding, however, is consistent with the premise that the gender gap disappears or diminishes significantly once the researcher controls for the differences in input use, market access, human and physical capital. Similar findings are also reported by Gilbert et al. (2012) and Goldstein and Udry (2008).

As expected, average precipitation during the rainy season is positively and significantly associated with maize productivity in all the specifications. However, the relationship seems to display an inverted U-shape behaviour as indicated by the coefficient of rainfall-square. Experiencing drought in the past year is also negatively related to maize productivity in the current year. We also find that farm households who have access to irrigation produce significant higher maize yield per unit of land compared to households without access to irrigation. Plots with access to irrigation have about 40-75% more in maize productivity compared to plots without irrigation and this difference is statistically significant in all the specification with only one exception. Contrary to our expectation, plot quality is negatively related with maize productivity, however as expected the plots that have high exposure to erosion tend to display lower productivity.

Results also show an inverse relation (IR) between plot size and productivity of maize which is consistent with many other findings in the literature. The coefficients of both plot size and square of plot size are negative and highly significant in all the specifications. Results of negative effect of size on productivity (IR) have been mostly explained by imperfect land and labour markets and in particular family labour surplus on small farms that increases labour input per land and subsequently output per land (e.g. Newell et al., 1997; Reardon et al., 1996). Further explanation of IR is related to errors in land measurements. For the IR to be partially or fully explained by errors in land measurements, smaller farmers would have to systematically underreport land area with respect to larger farmers, thus resulting in artificially inflated yields in the bottom part of the distribution. Contrary to earlier conjectures, Carletto et al. (2013) find that the empirical validity of the IR hypothesis is strengthened, not weakened, by the availability of better measures of land size collected using

GPS devices in Uganda. Given that we also used plot measurements collected using GPS devices, our findings are consistent with Carletto et al. (2013).

After controlling for the endogeneity problem using IV technique, the analysis reveal that on average adoption of each of the five farm management practices has a positive and statistically significant impact on quantity of maize produced per acre of land suggesting the positive synergies between adaptation/risk-mitigating strategies and food security. For adoption of improved maize seed, the overall average gain of adoption is about 0.98, which is about 98% increase in quantity of maize produced per acre of land for adopters compared to the non-adopters. As also expected adoption of inorganic fertilizer has a significant positive effect on productivity of maize. Farmers adopting of maize-legume intercropping gains about 80% more maize produced per acre of land compared to farm households who did not adopt. The same story holds true for adoption of planting tree and SWC measures – about 73% and 54% increase in maize productivity for adopters compared to the non-adopters. In all of the estimated coefficients, the IV estimates are higher than the OLS estimate which suggest that OLS approach would have underestimated the true impact of adoption of these farm management practices. Nevertheless, it is comforting to observe that the results for the adoption variables are qualitatively unaffected across all specifications (in the sense that the directional changes in the quantitative results are the same as before)

< Table 6 ABOUT HERE>

5. Conclusions and policy implications

The study utilizes farm household level data collected in 2011 from a nationally representative sample of 7842 households (11208 plots) to identify the factors governing farmers' decision to adopt adaptation/risk-mitigating strategies and estimate the adoption impacts of specific farm practices on maize productivity. We employ a multivariate probit (MVP) technique to model simultaneous and interdependent adoption decisions by farm households and utilize instrumental variable regression to estimate the casual impact.

Four main conclusions can be drawn from the results of this study. First, we find robust evidence that the propensity of adopting a specific practice is conditioned by whether a practice in the subset has been adopted or not. Besides justifying the use of MVP in comparison to the restrictive single equation approach, these results support the notion of interdependency between adoption decision of different farm management practices which may be attributed to complementarities or substitutability between the practices. The MVP results show that the adoption decisions of different farm practices are quite distinct and to a larger extent the factors governing the adoption decision of each of the farm management practices are also different. The results suggest the heterogeneity in adoption of farm management practices and accordingly, the unsuitability of aggregating them into one adaptation/ risk-mitigating variable.

Second, although household wealth proxies such as livestock holding, wealth index and agricultural implements index have differentiated impact on adoption, results overall point to the positive role of household wealth on the adoption decision suggesting that the higher the capacity of the household to absorb risk and finance an investment in additional activities, the greater the likelihood of adoption. Plot size, however, is negatively related with adoption of the SWC, maize-legume intercropping, planting tree and use organic fertilizer but positively correlated with inorganic fertilizer suggesting that larger farms appear to use more short-term inputs while households with smaller farm engage more on less capital intensive and traditional technologies. Better tenure security increase the likelihood that farmer adopt strategies that will capture the returns from their investments in the long run and reduces the demand for short-term inputs like inorganic fertilizer and improved seed.

Third, our findings suggest that favourable rainfall outcome affect positively the decisions to adopt short-term inputs such as improved seed types and inorganic fertilizer use whereas unfavourable rainfall outcome encourages farmer to adopt planting trees, maize-legume intercropping, use of organic fertilizer and SWC measures which in turn helps in conserving soil moisture, improve soil organic matter and reduce soil loss from erosion and flooding. Based on this evidence that climatic condition plays an important role in farmers' adoption decisions, it is natural to conclude that improving the access to reliable climate forecast information is key to facilitating adaptation. Linking farmers to new sources of information on climate variability will be important, but translating the risks and potential margin of error that exist in a way that farmer scan understand and use in making decision is equally important.

Fourth, access to extension advice and presence of organizations/institutions within the community (e.g. development committees and/or credit and savings organizations) affect positively the adoption of maize-legume intercropping, SWC and tree planting suggesting the importance of information and networks. Collective action also affect positivity the adoption of farm management practices that have public goods spillover (such as SWC) and less on practices with limited spillover consistent with theory of collective action. Also as expected the receipt of fertilizer and improved maize coupon (participation in farm input subsidy program) are positively related to the use of both inputs. The bottom line is that both formal and informal institutions matter in governing farmers adoption decisions to adapt to climate change. One key role of institutions is the production and dissemination of knowledge and information and by increasing uncertainty climate change increases the value of information and the importance of institutions that generate and disseminate it. It is therefore imperative to strengthen and improve the existing institutions providing extension service both in terms of coverage and efficiency and also at the same time building on existing social capital and networks by linking to external formal and informal institutions.

The final piece of evidence comes from the impact estimates. We find that on average adoption of each of the five farm management practices has a positive and statistically significant impact on quantity of maize produced per acre of land suggesting the positive synergies between adaptation/risk-mitigating strategies and food security.

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Table 1. Descriptive summary of adoption of adaptation practices – in proportion

Variables	North province (N=1897)		Central province (N= 3697)		Southern province (N=5614)		Total (N=11208)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Improved seed	0.554	0.497	0.530	0.499	0.476	0.499	0.507	0.500
Maize-legume intercropping	0.104	0.306	0.077	0.266	0.355	0.479	0.221	0.415
Tree planting	0.511	0.500	0.275	0.447	0.426	0.494	0.390	0.488
Organic fertilizer	0.072	0.259	0.168	0.374	0.109	0.311	0.122	0.327
Inorganic fertilizer	0.747	0.435	0.785	0.411	0.724	0.447	0.748	0.434
SWC measures	0.377	0.48	0.477	0.49	0.46	0.49	0.45	0.49

Note: The number of observation here refers to number of maize plots

Table 2. Maize productivity by adoption status (kg/acre)

Variables	North province (N=1897)		Central province (N= 3697)		Southern province (N=5614)		Total (N=11208)	
	Mean	Std. Err.	Mean	Std. Err.	Mean	Std. Err.	Mean	Std. Err.
Maize-legume intercrop								
No	601.2	12.9	347.5	7.1	587.6	16.9	496.4	8.0
Yes	1164.7	70.4	460.1	28.4	821.7	23.7	807.8	20.4
Difference (%)	93.7(12.5)***		32.4(4.3)***		39.8(8.1)***		62.7(16.7)***	
Tree planting								
No	693.3	21.6	350.5	8.0	667.1	20.2	546.5	10.6
Yes	628.1	18.7	370.7	13.8	675.8	17.8	594.3	11.2
Difference (%)	-9.4(2.2)**		5.7(1.2)		1.3(0.3)		8.7(2.9)***	
SWC measures								
No	647.1	18.0	381.5	10.1	600.2	18.9	540.5	10.5
Yes	681.3	23.3	328.3	9.4	754.0	20.2	595.1	11.6
Difference (%)	5.3(1.1)		-13.9(3.8)***		25.6(5.5)***		10.1(3.4)***	
Improved seed								
No	646.4	22.6	294.9	8.3	566.8	15.0	493.6	9.3
Yes	671.0	18.2	410.2	10.7	785.4	23.8	634.7	12.4
Difference (%)	3.8(0.8)		39.1(8.3)***		38.6(7.9)***		28.6(9.0)***	
Inorganic fertilizer								
No	536.5	24.1	267.2	11.3	339.6	11.6	352.7	8.4
Yes	701.8	17.1	380.4	8.2	797.2	18.2	636.8	9.9
Difference (%)	30.8(5.0)***		42.3(6.7)***		134.7(15.0)***		80.5(15.9)***	

Note: Number of observations refers to the number of maize plots. *** p<0.01, ** p<0.05, * p<0.1. t-stat in parenthesis.

Table 3. Descriptive summary of selected variables

Variables	Northern province (N= 1404)		Central province (N= 2871)		Southern province (N=3567)		Total (N=7842)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Household level indicators								
Age of household head (years)	44.51	15.91	42.83	16.14	42.98	16.86	43.20	16.44
Gender of household head (1=male)	0.79	0.41	0.78	0.42	0.71	0.45	0.75	0.43
Household size (AE)	4.10	2.00	4.01	1.86	3.63	1.73	3.85	1.84
Sex ratio	1.19	0.97	1.16	0.97	1.16	0.99	1.17	0.98
Dependency ratio	1.19	0.96	1.24	0.92	1.22	1.00	1.22	0.96
Household head can read/write Chichewa (yes=1)	0.74	0.44	0.64	0.48	0.60	0.49	0.64	0.48
Household head highest level of education (years)	6.58	3.81	4.93	3.79	4.58	4.01	5.06	3.96
Spouse has attended school (1=yes)	0.67	0.47	0.56	0.50	0.46	0.50	0.53	0.50
Livestock ownership (tropical livestock unit (TLU))	1.12	2.91	0.54	2.36	0.46	2.59	0.61	2.58
Participate in off farm activities (1=yes)	0.19	0.39	0.18	0.38	0.19	0.39	0.18	0.39
Wealth index	0.15	1.83	-0.38	1.75	-0.45	1.64	-0.31	1.73
Agricultural implements access index	0.68	1.25	0.69	1.44	0.20	1.11	0.47	1.29
Fertilizer coupon (1=yes)	0.57	0.50	0.53	0.50	0.57	0.50	0.55	0.50
Maize coupon (1=yes)	0.36	0.48	0.16	0.36	0.25	0.43	0.24	0.42
Drought is a top three shock in the past year (1=yes)	0.21	0.40	0.07	0.25	0.52	0.50	0.30	0.46
Plot level characteristics								
Land tenure (1= own, 0= rented)	0.91	0.29	0.86	0.34	0.92	0.27	0.90	0.30
Soil quality of this plot (1= good)	0.44	0.50	0.46	0.50	0.46	0.50	0.46	0.50
Land size (acre)	2.20	1.69	2.46	1.95	3.12	2.95	2.71	2.45
Irrigation use (1=yes)	0.00	0.02	0.00	0.05	0.00	0.07	0.00	0.05
Extent of erosion on the plot (1=moderate/high)	0.18	0.38	0.12	0.33	0.10	0.30	0.12	0.32
Climatic and bio-physical variables								
Coefficient of variation of precipitation (1996-2011)	0.214	0.019	0.227	0.032	0.284	0.016	0.253	0.038
Precipitation in the rainy season (209/10) (mm)	891.8	70.7	691.6	73.2	661.8	39.6	710.6	101.3
Precipitation in the last rainy season (2008/09) (mm)	797.4	115.5	593.3	82.3	425.5	46.6	543.8	155.8
Agro-ecological suitability index for low-input maize	4418.4	1952.6	6976.4	2265.4	6643.0	1967.5	6376.4	2253.8
Potential production capacity for low-input maize	4161.6	2095.3	7066.0	2871.0	7102.7	2292.2	6592.8	2701.3
Community level indicators								
Number of months main road was passable by a lorry	9.47	4.52	10.21	2.84	9.55	3.50	9.78	3.51
Distance to major district centre (Km)	180.11	108.57	120.18	52.63	91.88	84.39	118.04	85.82
Distance to a daily market (Km)	14.55	16.50	5.81	7.60	9.27	13.04	8.95	12.51
Village development committees in the community (number)	1.69	1.95	2.42	3.11	2.06	3.28	2.12	3.03
Saving & credit organisation in the community (number)	0.14	1.94	0.40	1.56	0.37	2.34	0.34	2.01
Proportion of households with access to extension advice in the community	59.72	29.12	50.38	28.56	45.40	25.35	49.79	27.73
Collective action index	-0.07	0.84	0.39	1.20	-0.12	0.80	0.07	1.00
DPP vote as a share of total vote cast	0.95	0.03	0.54	0.18	0.71	0.22	0.69	0.24
MCP vote as a share of total vote cast	0.03	0.02	0.42	0.18	0.26	0.21	0.28	0.23

Note: dependency ratio = (family size – total workforce)/total workforce; sex ratio = female to male household members. Number of observations refers to the number of maize producing households.

Table 4. Estimated covariance matrix of the regression equations between the adaptation measures using the MVP joint estimation model

	Improved seed	Inorganic fertilizer	Organic fertilizer	Tree planting	Maize-legume intercropping
Inorganic fertilizer	0.172 (0.017) ***				
Organic fertilizer	-0.003 (0.02)	-0.097 (0.022)***			
Tree planting	-0.006 (0.016)	0.027 (0.018)	0.058 (0.021)***		
Maize-legume intercropping	-1.021 (0.026)***	0.065 (0.02)***	0.069 (0.024)***	0.046 (0.019)**	
SWC measures	0.005 (0.016)	0.056 (0.017)***	0.072 (0.02)***	0.074 (0.016)***	0.079 (0.018)***
Likelihood ratio test of rho21 = rho31 = rho41 = rho51 = rho61 = rho32 = rho42 = rho52 = rho62 = rho43 = rho53 = rho63 = rho54 = rho64 = rho65 = 0: chi2(15) = 2367.65 Prob > chi2 = 0.0000					

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parenthesis.

Table 5. Results of the multivariate probit model – barrier to adoption of adaptation measures

	Tree planting		Maize-legume intercrop		SWC		Organic fertilizer		Improved seed		Inorganic fertilizer	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Coefficient of variation of precipitation (1996 -2011)	2.388***	0.001	-0.055	0.001	-2.975***	0.000	-3.006***	0.001	-0.109	0.614	-1.131*	0.179
Agro-ecological suitability index for low-input maize	-0.000***	0.653	0.000	0.805	-0.000	0.632	0.000***	0.800	0.000***	0.000	-0.000	0.001
Precipitation in the last rainy season (mm)	-0.001***	0.000	-0.003***	0.000	-0.001***	0.000	-0.001***	0.000	0.001***	0.000	0.000	0.688
Drought is a top three shock in past year	0.126***	0.000	-0.016	0.000	0.177***	0.000	-0.038**	0.000	-0.075***	0.016	-0.103***	0.000
Age of household head (years)	0.010***	0.033	0.004***	0.037	-0.001	0.032	0.002**	0.041	-0.010***	0.001	-0.007***	0.005
Gender of household head (1=male)	-0.046	0.001	-0.113***	0.001	0.055	0.001	-0.114**	0.001	0.205***	0.039	0.023	0.036
Household size (AE)	0.025***	0.012	0.013	0.013	-0.005	0.012	0.009	0.015	-0.011	0.009	-0.053***	0.000
Sex ratio	-0.009	0.008	0.010	0.009	0.085	0.007	-0.163**	0.009	0.161***	0.063	0.030	0.014
Dependency ratio	0.016	0.065	-0.032**	0.073	-0.031**	0.063	0.005	0.082	-0.013	0.014	-0.014	0.009
Head can read/write Chichewa (yes=1)	-0.005	0.014	0.134***	0.016	0.242***	0.014	-0.042	0.017	0.009	0.038	-0.048	0.068
Household head education (years)	0.007	0.038	-0.021***	0.043	-0.004	0.037	0.009	0.047	0.009*	0.005	0.013**	0.015
Spouse has attended school (1=yes)	0.024	0.005	-0.024	0.006	0.018	0.005	0.131***	0.006	-0.043	0.032	0.042	0.041
Plot size (acre)	-0.098***	0.006	-1.163***	0.006	-0.055**	0.006	-0.052*	0.006	0.041	0.032	0.139***	0.005
Land tenure (1= own, 0= rented)	0.407***	0.240	0.354***	0.273	0.037	0.233	0.273***	0.234	-0.343***	0.045	-0.622***	0.001
Soil quality of this plot (1= good)	-0.140***	0.047	-0.071**	0.055	-0.098***	0.043	-0.063**	0.058	-0.036	0.025	-0.062**	0.254
Extent of erosion of this plot (1=moderate/high)	0.143***	0.026	0.030	0.029	0.756***	0.025	0.039	0.032	-0.013	0.038	-0.168***	0.058
Irrigation use (1=yes)	-0.077	0.001	-0.447	0.001	0.446*	0.001	0.634***	0.001	0.163	0.224	0.690***	0.000
Livestock size (TLU)	-0.007	0.039	0.029***	0.045	0.023**	0.039	0.050***	0.049	0.013	0.010	-0.028***	0.027
Wealth index	-0.005	0.010	-0.020**	0.011	0.020**	0.010	0.019*	0.011	0.092***	0.009	0.229***	0.041
Agricultural implements access index	0.152***	0.009	0.042***	0.010	0.086***	0.008	0.083***	0.010	-0.075***	0.015	-0.045***	0.010
Proportion of households with access to extension advice (on the specific practices) in the community	0.007***	0.075	-0.002***	0.102	0.000	0.076	-0.002***	0.100	0.002**	0.001	0.001**	0.085
Collective action index	-0.047***	0.011	0.023	0.013	0.029**	0.010	0.055***	0.013	0.004	0.013	-0.049***	0.013

Number of village development committees in the community	0.010**	0.014	0.001	0.016	0.029***	0.013	0.013***	0.017	-0.008*	0.005	-0.005	0.013
Number of credit and saving organization in the community	0.029***	0.004	0.012**	0.005	-0.006	0.004	0.003	0.005	-0.003	0.006	-0.000	0.015
Number of months the main road was passable by a lorry	0.013***	0.038	-0.009**	0.042	-0.006*	0.037	0.003	0.047	-0.004	0.004	0.010**	0.001
Distance to major district centre (Km)	-0.000	0.004	0.001***	0.004	-0.001***	0.004	-0.000	0.005	-0.001***	0.000	-0.000	0.040
Distance to a daily market (Km)	-0.001	0.000	0.003***	0.000	0.001	0.000	0.001	0.000	-0.007***	0.001	-0.003***	0.004
Price of maize grain (MK/kg)	-0.002**	0.027	-0.002**	0.044	-0.001	0.025	0.002***	0.031	0.002***	0.001	0.001**	0.007
Residual for maize coupon receipt									2.340***	0.330		
Residual for fertilizer coupon receipt											2.892***	0.062
Northern province (reference)												
Central province	-0.161***	0.001	-0.522***	0.001	0.253***	0.001	0.301***	0.001	0.463***	0.064	0.303***	0.030
Southern province	0.171**	0.055	-0.163	0.079	0.116	0.054	0.110	0.073	0.272***	0.074	0.109	0.001
Constant	-2.280***	0.284	1.174***	0.353	0.595**	0.273	-0.720**	0.356	-0.668**	0.012	0.358	0.315
Log-Likelihood	-34335.77											
LR test of rho=0 : Chi2 (182)	6440.41 ***											
Number of observations (plot)	11206											

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at household level.

Table 6. Impact of adoption of adaptation practices on maize productivity (log of quantity produced per acre)

	OLS		Instrumental Variable (IV) Regression									
	(1)		(2)		(3)		(4)		(5)		(6)	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Household size (AE)	-0.008	0.009	0.011	0.011	-0.002	0.011	-0.005	0.009	-0.009	0.010	-0.003	0.010
Sex ratio	-0.096	0.074	-0.011	0.085	-0.149	0.097	-0.067	0.075	-0.066	0.077	-0.083	0.077
Dependency ratio	0.002	0.016	-0.004	0.018	0.024	0.022	-0.002	0.016	-0.012	0.017	-0.000	0.017
Head can read/write Chichewa (yes=1)	0.080**	0.041	0.190***	0.050	0.060	0.058	0.101**	0.043	0.133***	0.043	0.084*	0.047
Household head education (years)	0.001	0.005	0.010	0.006	-0.012	0.009	0.007	0.005	0.002	0.005	0.005	0.005
Spouse has attended school (1=yes)	0.135***	0.038	0.172***	0.044	0.075	0.058	0.153***	0.039	0.162***	0.040	0.157***	0.040
Age of household head (years)	-0.001	0.001	-0.003**	0.001	-0.003*	0.002	-0.001	0.001	-0.002**	0.001	0.000	0.001
Gender of household head (1=male)	-0.100**	0.043	-0.058	0.050	-0.094*	0.053	-0.082*	0.044	-0.115**	0.045	-0.132***	0.045
Precipitation in rainy season 2009/2010 (mm)	0.025***	0.002	0.026***	0.003	0.015***	0.006	0.027***	0.002	0.028***	0.003	0.027***	0.003
Precipitation square	-0.000***	0.000	-0.000***	0.000	-0.000**	0.000	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000
Drought is a top three shock in past year (yes=1)	-0.123***	0.016	-0.125***	0.018	-0.059*	0.032	-0.126***	0.016	-0.155***	0.017	-0.155***	0.021
Irrigation use (yes=1)	0.647***	0.197	0.415	0.260	0.750***	0.242	0.621***	0.210	0.526***	0.201	0.424**	0.214
Plot size (acre)	-0.603***	0.031	-0.795***	0.038	-0.439***	0.128	-0.641***	0.034	-0.752***	0.034	-0.751***	0.034
Plot size square (acre)	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000
Soil quality of this plot (1= good)	-0.104***	0.030	-0.132***	0.035	-0.152***	0.037	-0.109***	0.031	-0.076**	0.031	-0.098***	0.032
Extent of erosion of this plot (1=moderate/high)	-0.225***	0.047	-0.243***	0.051	-0.103	0.076	-0.230***	0.047	-0.259***	0.048	-0.381***	0.081
Wealth index	0.096***	0.009	0.180***	0.011	-0.041	0.073	0.142***	0.009	0.140***	0.009	0.133***	0.009
Agricultural implements access index	-0.016	0.012	0.007	0.013	-0.013	0.017	-0.003	0.012	-0.032**	0.013	-0.012	0.014
Collective action index	0.018	0.015	0.034*	0.018	0.044**	0.022	0.016	0.016	0.017	0.016	0.011	0.016
Livestock size (TLU)	-0.018	0.025	-0.012	0.025	-0.009	0.025	-0.020	0.025	-0.015	0.026	-0.021	0.025
Labour per acre (man-days)	0.001	0.001	0.003***	0.001	-0.003	0.002	0.002***	0.001	0.002***	0.001	0.002***	0.001
Labour per acre square (man-days)	0.000	0.000	0.000	0.000	-0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Pesticides/herbicides use (yes=1)	0.086	0.175	0.109	0.217	0.040	0.234	0.126	0.176	0.039	0.176	0.053	0.175
Distance to major centre (Km)	-0.001***	0.000	-0.001***	0.000	-0.000	0.000	-0.001***	0.000	-0.001***	0.000	-0.001***	0.000

Distance to a daily market (Km)	0.005***	0.001	0.004***	0.001	0.005***	0.001	0.004***	0.001	0.007***	0.001	0.005***	0.001
Number of village development committee	0.004	0.004	0.014***	0.005	-0.006	0.010	0.008*	0.004	0.008**	0.004	0.004	0.005
Number of credit and saving organization	0.013**	0.006	0.016*	0.009	0.017**	0.008	0.013*	0.007	0.009	0.007	0.018***	0.006
Agro-ecological suitability index for low-input maize	0.000	0.000	-0.000	0.000	0.000	0.000	-0.000	0.000	0.000**	0.000	-0.000	0.000
Northern province (reference)												
Central province	-0.321***	0.060	-0.159**	0.076	-0.165	0.115	-0.309***	0.061	-0.344***	0.065	-0.405***	0.065
Southern province	-0.211***	0.063	0.013	0.078	0.116	0.144	-0.255***	0.065	-0.224***	0.069	-0.158**	0.067
Improved seed (yes=1)	0.258***	0.030	0.983*	0.538								
Fertilizer use per acre (kg)	0.004***	0.000			0.019**	0.008						
Maize-legume intercrop (yes=1)	0.545***	0.040					0.804***	0.087				
Tree planting (yes=1)	0.172***	0.032							0.726***	0.084		
SWC measures (yes=1)	0.061*	0.031									0.541**	0.229
Constant	-3.973***	0.972	-3.767***	1.052	-0.888	1.677	-4.443***	0.979	-4.950***	1.014	-4.537***	1.028
Number of observations (plots)	11026		11026		11026		11026		11026		11026	
Log-Likelihood	-		-26564.98		-		-23863.29		-25837.53		-26259.18	
R-square	0.247		-		0.131		-		-		-	
Wald chi2(31)/F-test	79.32		20262.8		47.4		2188.4		1935.5		1943.8	
Prob > chi2/F	0.000		0.000		0.000		0.000		0.000		0.000	
athrho			0.762***				-0.180***		-0.253***		-0.192*	
lnsigma			0.436***				0.293***		0.309***		0.303***	
LR test of indep. eqns. (rho = 0): Prob > chi2			0.000				0.000		0.000		0.071	

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at household level