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Abstract

Farm-level adoption of a portfolio of climate-smart agricultural (CSA) practices remains important to climate change adaptation and agricultural development in Sub-Saharan Africa. This paper uses nationally representative panel data sets in rural Nigeria to understand farm households' decisions on choices of a range of CSA practices – such as cropping system diversification, improved seeds, and inorganic and organic fertilizers – and assess their combined effect on net farm returns using an endogenous switching treatment effects method. Our results reveal that adoption of CSA practices differs according to the level of asset ownership and incidence of shocks. While adoption of an individual CSA practice increases income compared with non-adoption, the highest farm income was achieved when farmers adopted all practices jointly. We conclude that adoption of multiple CSA practices can enhance farm income.

Key Words: climate-smart agriculture; farm income; climate change; panel data; Nigeria.

JEL Codes: Q12, Q54

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1. Introduction

In Sub-Saharan African countries, smallholder farmers are challenged with frequently changing patterns of temperature and precipitation and increased occurrences of extreme events such as droughts and floods. Climate change is projected to reduce yields and income from agriculture in the region by about 90% in 2100 (IPCC, 2007). In Nigeria in particular, changes in temperature and precipitation patterns expose the country's agricultural production systems to tremendous climate risks causing crop failures and production declines. Findings from historical climate and yield data in Nigeria show that temperature and precipitation changes have reduced maize and rice yields and increased the variability of yields (Aye and Ater, 2012).

Climate change is adding pressure to the already stressed ecosystems in which smallholder farming takes place. These farmers face overlapping constraints, such as moisture stress, loss of soil fertility, pest and diseases, etc. These constraints pose a challenge to intensification of agricultural production through crop management alternatives such as adoption of external inputs (improved seeds and fertilizer). Appropriate climate-smart agricultural (CSA) practices are important to enhance productivity in agriculture, ensure resilience to climatic stresses, and sustainably reduce greenhouse gas (GHG) emissions from agricultural production (FAO, 2010). Yet, adoption remains below optimal levels. Therefore, a better understanding of the drivers of adoption of multiple CSAs and their impact remains a critical challenge to climate change adaptation and agricultural development in Sub-Saharan Africa. Yet, much less is known about the impact of climate change on the activities of other important actors along commodity value chains.

In this study, we explore how farmers make the choice of four agricultural practices – cropping system diversification, modern seeds, and inorganic and organic fertilizer – and the impact of the different combinations of these practices on farm income. We build on recent studies (Aryal et al., 2018; Di Falco and Veronesi, 2013; Isaahaku and Abdulai 2019; Kassie et al., 2015; Kassie et al., 2017; Ng'ombe et al., 2017; Teklewold et al., 2017; Teklewold et al., 2019) that argue that farmers can benefit by adopting multiple practices jointly so as to exploit the potential advantages of complementarity to deal with the overlapping constraints discussed above. In complex smallholder farming systems, analysis made without considering such interdependence may bias the estimation of the influence of several factors on the decision to adopt the practices (Hassan and Nhemachena 2008; Wu and Babcock, 1998).

There is worldwide recognition of the potential benefits of cropping system diversification in terms of increasing farm productivity, reducing risk of crop failure, and increasing year-round employment (Tilman et al., 2002). However, to the best of our knowledge, no studies have focused specifically on smallholder agricultural intensification that requires joint adoption of integrated land and crop management alternatives. Hence, we examine the potential complementarity of these crop and land management practices. Our novel contribution is investigating whether adoption of a combination of these climate-smart practices will provide more economic benefits than adopting them individually.

Cropping diversification is a strategy for growing more than one crop across space or time which involves the exploitation of jointly beneficial interactions among individual crops. These include reducing the incidence of weeds, pests and diseases; improving soil fertility, organic matter content, and water-holding capacity; diversifying seasonal requirements for resources; and stabilizing farm income over time through evening out the impact of price fluctuations (Jhamtani, 2011; Liebman and Dyck, 1993; Snapp et al., 2010; Tilman et al., 2002). This practice is often considered a key component of integrated soil fertility management and integrated pest management strategies for smallholder farmers. Crop diversification also allows farmers to cultivate crops that can be harvested at different times and in different places, and that have different weather or environmental stress-response characteristics. Hence, multiple cropping serves as a good strategy to mitigate the effects of drought and to increase water use efficiency, while increasing the overall yield of the cropping system (Kar et al., 2004). If cropping system diversification is combined with other farm technologies such as modern crop varieties and fertilizer, farm production can use ecosystem services more efficiently.

Improved seeds and inorganic fertilizer are climate-smart agricultural practices that can increase farm income for a rapidly growing population by improving farm productivity (Brown and Funk, 2008). Improved farm productivity increases resilience to climate variability and hence is an important strategy in adaptation to future climate change (Bryan et al., 2011). Moreover, appropriate use of fertilizer is required, both to enhance crop productivity and to produce sufficient crop residues to ensure soil cover under smallholder conditions (Vanlauwe et al., 2013). Research on adoption of modern crop varieties and fertilizer can inform strategies for adapting to climate change. However, relatively little rigorous work on adaptation has been carried out; expanding this knowledge is a further contribution of this paper.

The use of organic fertilizer refers to the application of compost and livestock wastes on the farming plot. It is a major component of sustainable agricultural systems, with the potential benefits of long-term maintenance of soil fertility through supplying soil nutrients, especially nitrogen, phosphorus and potassium. The application of organic fertilizers can increase soil organic matter content, which leads to improved water infiltration and soil-water holding capacity. Improving soil organic matter enables the removal of atmospheric CO_2 by allowing the land to serve as a carbon sink (Marenya and Barrett 2009). All these have implications for climate change mitigation and adaptation.

The paper is organized as follows. Section 2 provides a brief description of the survey and summarizes the data used in the analysis. Section 3 presents the conceptual and econometric framework. Section 4 presents our estimation results on the determinants of choice of CSA practices and their impact on net farm income. The final section concludes and draws key policy implications.

2. Data and Methods

2.1 Survey description

The data for this study is obtained from the Nigeria General Household Survey (GHS) panel data sets collected in 2011/2012, 2013/2014 and 2015/2016. The data set was collected from a nationally representative survey of 5000 households and it covers all agricultural periods. The GHS sample comprises 60 Primary Sampling Units (PSUs) or Enumeration Areas (EAs) which were selected from each of the 37 states in Nigeria. This gives a total of 2,220 EAs nationally. Each EA contributes 10 households to the GHS sample, resulting in a sample size of 22,200 households. Out of the 22,000 households, 5,000 households from 500 EAs were randomly selected to establish the panel component in the consecutive survey periods. Out of the 5000 households, 4,997 households completed the interview in wave one, 4746 in wave two and 4611 in wave three. This attrition is because some households moved, especially as a result of the poor security situation in North East Nigeria. The overall attrition rate between wave one and three is about 8 percent.

In all rounds of the survey, a questionnaire containing different types of modules was administered. These included a household module asking questions about livelihood, household composition, socioeconomic status, and shocks, and a community module seeking information on geographic location and climate characteristics. Households were also asked whether they had applied different agricultural practices and technologies on each of their farming plots in the study period. They also were asked the details of farm input utilization, output obtained, and farm revenue generated[1]. The survey also recorded geo-referenced household level latitude and longitude coordinates, allowing us to link household-level data to historical temperature and precipitation data.

[1] Our outcome indicator is net farm income, after input costs (fertilizer, seed, labour and pesticides) have been accounted for. This is used instead of crop yield to address the problems of multiple cropping and cost differences across practices.

2.2 Descriptive statistics

Choice variables – climate smart agricultural practices

Table 1 depicts the adoption rate of the different CSA practices (cropping system diversification, modern seeds, inorganic and organic fertilizers) in each year of the survey.
The adoption patterns and the frequency of responses for each strategy across the whole sample and for each survey year show that adoption of multiple strategies is common among households in the study areas. On average, cropping system diversification, improved crop seeds, inorganic and organic fertilizer were used on 82, 68, 40 and 15% of the plots, respectively. Table 2 reports a series of binary triplets that highlight the different combinations of strategies that be considered as partial adoption. On average, about 95% of households adopted one or more of the CSA strategies. Close to 1% of the households adopted the four practices jointly while less than 17% of households employed only one of these strategies. The sample unconditional and conditional probabilities presented in Table 3 also highlight the existence of interdependence across the four practices. For instance, the probability of adopting cropping system diversification and inorganic fertilizer respectively increased by 8 and 15% conditional on adoption of organic fertilizer. The conditional probability of household adopting cropping system diversification and organic fertilizer increased by 3 and 5%, respectively, when farmers applied inorganic fertilizer.

A non-parametric net farm income distribution analysis showed that all the CSA practices considered in this study impact the net value of farm production. However, across all these CSA practices, the cumulative distribution of the net value of farm production on plots with cropping system diversification, modern seeds, inorganic or organic fertilizer do not uniformly dominate the net farm income cumulative distribution on plots without any of these CSA practices. This is shown by the graphs (Figure 1) of the cumulative density function (CDF) of net farm income with one or more CSA practices, which are not constantly below or equal to that of plots without any of these practices.

Control variables

Summary statistics of the variables used in the econometric analysis are reported in Table 4, disaggregated by non-adopters and adopters of CSA practices. The choice of the explanatory variables in our model specification is based on previous literature on farmers' adoption of various types of agricultural practices and technologies (Aryal et al. (2018); Isaahaku and Abdulai (2019);

Kassie et al. (2014); Kassie et al. (2017); Ng'ombe et al. (2017); Teklewold et al (2013); and Teklewold et al. (2019).

The main covariate and idiosyncratic risk factors considered are climatic variables, health shock, and pest attack. We construct shocks dummy variables based on self-reported responses to questions related to different types of idiosyncratic shocks. Responses to each of these questions (either yes or no) were coded as unfavorable or favorable outcomes, respectively. To control for the covariate climatic shocks, we derived long-term mean rainfall and temperature variables and included them in the regression model. This is obtained from the survey that recorded geo-referenced household-level latitude and longitude coordinates using Global Positioning System (GPS) devices, which allows for the linking of household-level data to these historical climate variables (temperature and rainfall).

We include size of farm land and livestock ownership (in Tropical Livestock Units, TLU) as a measure of household wealth and to control for a household's response to risk exposure (Morduch 1995). Both are indicators of the household's dependence on agriculture and rainfall. A common indicator to proxy income diversification is the income derived from off-farm employment and remittance income. We therefore include a dummy variable equal to 1 if the household received a remittance in the form of cash and/or participated in off-farm work, as an indicator of additional income, which could influence adoption of CSA practices. Often, rural households diversify their sources of income in order to smooth their income and consumption (Barrett et al., 2001) or to relax liquidity constraints in implementing adaptation practices (Teklewold et al., 2019). We explore how the households' off-farm participation and incidence of remittance have an effect on choice of CSA strategies. We considered household's access to road and market and their demographic characteristics as proxies for access to information and market opportunities. Access to such infrastructure is measured by the average distance to reach the nearest road and input and output market; limited access can negatively influence adoption by increasing travel time and transport costs.

We include some plot-specific attributes, including number of parcels, plot slope, plot elevation, plot wetness, and spatial distance of the plot from farmer's residence. About 90% of landowners operate on up to nine parcels of land, each with about 2.5 ha, and these plots are often not spatially adjacent. The variable distance to plot is an important determinant of adaptation practices through its effect on increasing transaction costs on the farthest plot, particularly transporting bulky inputs. For instance, plots that receive organic fertilizer tend to be closer to home (about 1.3 km) than plots with the other practices (about 2.5 km). Distant plots usually receive less attention and are difficult to monitor; this makes it less likely that farmers will adopt diversification, particularly of cereal and legume crops. We also controlled for the agro-ecological zone where the household is located. Different agro-ecological zones may affect the type and combination of CSA practices.

2.3 Econometric Approach and Model Specification

Simultaneous endogenous switching regression

We used an empirical method that models farmers' decisions regarding the adoption of a portfolio of CSA practices and simultaneously models the influence of the CSA practices on farm returns. It is assumed that farm households choose a single adaptation strategy or a combination of strategies that maximizes the expected utility conditional on the decision. Thus, the adoption decision is inherently multivariate, and the approach using univariate modeling often doesn't show important economic information contained in interdependent decisions (Kassie et al., 2015; Teklewold et al., 2013). Our approach recognizes that the same unobserved characteristics of farmers could influence the adoption of the various strategies and therefore is more efficient than the univariate methods of analyzing adoption of each strategy independently. Thus, the choice of various combinations of CSA actions and their implications for farm return is analyzed by applying a two-stage estimation procedure (Bourguignon et al., 2007), using endogenous switching regression with a multivariate probit model (MVP). In the first stage, a multivariate probit model is used to analyze the determinants of the adoption decisions. In the second stage of the estimation, the impacts of adopting various CSA strategies for farm income outcome are analyzed.

This study recognizes that differences in farm income between those households that did and did not adopt CSA practices may be due to selection bias from observable and unobservable characteristics. We assume adoption of farm technologies among farmers are non-random, where adopters are likely to differ from non-adopters in the distribution of their observed household socioeconomic characteristics, resulting in selection bias on observables. This bias would arise because the adoption criteria can also be expected to influence farm income even in the absence of the coping strategies when using standard econometric approaches (e.g., ordinary least-squares). The second source of selection bias is from the difference in the distribution of unobservable characteristics between the adopters and non-adopters of the practices, where the unobservable factors, such as motivation and ability, affect both the choice of practices and the farm income. That is, the measured effect of the different strategies on the household outcomes may just be due to the difference in the unobservable characteristics, rather than being due to CSA adoption. The presence of unobserved heterogeneity in the outcome equations, if correlated with observed explanatory variables, can also lead to inconsistent estimates.

The endogenous switching regression combined with panel data can help avoid bias in the impact estimates and build a statistical comparison group of farmers akin to CSA adopters. The multivariate probit model employing Mundlak (1978) device is first estimated to find estimates of time-variant individual heterogeneity (Inverse Mills Ratios)[2] causing selection bias. The farm income equations are then estimated by fixed effects, including Inverse Mills Ratios estimates from the first stage as additional explanatory variables. The use of Mundlak in the first step and fixed effects approach in the second step capture time-invariant individual heterogeneity underlying endogeneity and Inverse Mills Ratios take care of time-varying heterogeneity. The Mundlak approach permits including the means of the time-varying covariates in the adoption equations as additional variables in the multivariate probit model, as a proxy for eliminating the time-invariant individual effects. Modeling this dependence permits unbiased estimation of the parameters, irrespective of whether or not the explanatory variables and the individual effects are independent in the equations (Ebbes et al., 2005).

Consider the i^{th} household $(i = 1,\dots, N)$ that is facing a decision on whether or not to adopt the available CSA practices. Let U_k represent the benefit of adopting the k^{th} practice, where k denotes the choice of different strategies such as cropping system diversification (C), improved seeds (V), inorganic fertilizer (F) and organic fertilizer (O); and let U_j represent the benefits to the household from non-adoption rather than the kth strategy. The household decides to adopt the k^{th} strategy if the associated utility, U_k outweighs the utility that could be obtained from non-adoption, U_j , such that $U_k > \max(U_j)$ where k=C, V, F, O and k≠j. The utility that the farmer derives from the adoption of the k^{th} practice is a latent variable determined by observed socioeconomic and climate variables and expressed as follows:

$$U^*_{itk} = X'_{it}\beta_k + \alpha + \varepsilon_{itk} \quad (\mathrm{k = C, V, F, O}) \quad . \qquad (1)$$

[2]The inverse Mill's Ratio is defined as the ratio between the standard normal probability distribution function and the standard normal cumulative distribution function. It is the selection term that captures all potential effects of the difference in unobserved variables.

where X'_{it} is a matrix of household characteristic and climate variables, β_k are parameters to be estimated, α is unobserved time-constant heterogeneity and ε_{itk} is the disturbance term.

Using the indicator function, the unobserved preferences in equation (1) translate into the observed binary outcome equation for each choice as follows:

$$I_{itk} = \begin{cases} 1 \text{ if } U^*_{itk} > 0 \\ 0 \text{ otherwise} \end{cases} \qquad (k = C, V, F, O) \quad . \qquad (2)$$

These selection equations estimate the probability of adopting CSA practices. Because simultaneous adoption of several practices is assumed, the system of equations from (2) is estimated using the multivariate probit model. The error terms jointly follow a multivariate normal distribution with zero conditional mean and variance normalized to unity (for identification of the parameters) where $(u_C, u_V, u_F, u_O) \sim MVN(0, \Omega)$ and the symmetric covariance matrix Ω is given by:

$$\Omega = \begin{bmatrix} 1 & \rho_{C,V} & \rho_{C,F} & \rho_{C,O} \\ \rho_{V,C} & 1 & \rho_{V,F} & \rho_{V,O} \\ \rho_{F,C} & \rho_{F,V} & 1 & \rho_{F,O} \\ \rho_{O,C} & \rho_{O,V} & \rho_{O,F} & 1 \end{bmatrix} \qquad (3)$$

where ρ (rho) represent the pairwise correlation coefficient of the error terms corresponding to any two CSA practice equations to be estimated in the model. Of particular interest are the non-zero off-diagonal elements in the variance-covariance matrix, which represent the occurrence of error terms correlation between the different equations. This assumption implies that equation (2) represents an MVP model that illustrates the decisions to adopt CSA simultaneously. A positive correlation of ρ is understood as a complementary association, while a negative relationship is taken as being alternates.

We also required estimating the outcome equations, conditional on households' decision to adopt different CSA practices. Because the decision to adopt the four practices in equation (2) is defined over the entire set of observations, then a simultaneous decision with sixteen possible classifications of groups would result, as shown in Table 2. Then, in the second step, the relationship between the farm income variables and a set of control variables is estimated by a fixed effect model for the chosen combination of CSA practices. The outcome equation for the j^{th} combination of practices is given as:

$$Y_{itj} = \delta Z_{itj} + \Phi_j + u_{itj} \qquad \text{if } I_{it} = j \qquad \text{for } j = 1, \ldots, J \qquad (3)$$

Here Y_{itj}'s are vectors of the outcome variable (net farm income) of the i^{th} farmer for CSA category j at time t and the error term $(u_{itj}$'s$)$ is distributed with $E(u_{itj}|X,Z)=0$ and $var(u_{itj}|X,Z)=\sigma_j^2$. Y_{itj} is observed if and only if CSA practice *j* is used; Z is a vector of covariates influencing farm income, and Φ is unobserved time-invariant household heterogeneity. From the estimation results of the multivariate probit model (equation 2), we derive the Inverse Mills Ratio (λ) variables that will be added as additional explanatory variables in the second-stage outcome equations (3) to capture individual heterogeneity underlying selection bias[3]. The second-stage equation of the endogenous switching regression in (3) is re-specified as:

$$Y_{itj} = \delta Z_{itj} + \sigma_j \hat{\lambda}_{itj} + \Phi_j + u_{itj} \qquad \text{if } I_{it} = j \qquad \text{for j= 1, . . . , J} \qquad (4)$$

where σ_j is the parameter of coefficients for $\hat{\lambda}_{itj}$ showing the covariance between ε's and u's.

Impact assessment

The predictions from estimation of the outcome equation (4) for each combination of practices are used to derive the conditional expectations and the average difference in net farm income between non-adopters and adopters of different CSA practices. These are given as follows. Average net farm income for adopters with adoption of the *j*th practice (this is what we actually observed in the sample):

$$E(Y_{ij} | I_i = j) = \delta_j Z_{ij} + \sigma_j \lambda_{ij} \qquad \text{for j= 2, . . . , J} \qquad (5)$$

Average net farm outcome for non-adopters without adoption (this is also actually observed in the sample):

$$E(Y_{i1} | I_i = 1) = \delta_1 Z_{i1} + \sigma_1 \lambda_{i1} \qquad \text{for j= 1} \qquad (6)$$

Average net farm outcome for adopters had they decided not to adopt (counterfactual):

$$E(Y_{i1} | I_i = j) = \delta_1 Z_{ij} + \sigma_1 \lambda_{ij} \qquad \text{for j= 2, . . . , J} \qquad (7)$$

Average net farm outcome for non-adopters had they decided to adopt (counterfactual):

$$E(Y_{ij} | I_i = 1) = \delta_j Z_{i1} + \sigma_j \lambda_{i1} \qquad \text{for j= 2, . . . , J} \qquad (8)$$

These expected values are used to compute unbiased estimates of the effects of adoption of a combination of CSA practices. The average adoption effect of CSA practices conditional on

[3]See Bourguignon *et al.* (2007) for the derivation of selection bias correction terms from the choice model.

adopters provides an estimate of the average treatment effect on the treated (ATT). This estimand answers the question of how the average net farm income would change if everyone who adopted a combination of CSA practices had instead not adopted the practices. The ATT is defined as the average difference in net farm income between adopters of CSA practices and their counterfactuals, given by the difference between Equations (5) and (7):

$$ATT = (Y_{ij} \mid I_i = j) - E(Y_{i1} \mid I_i = j) = Z_{ij}(\delta_j - \delta_1) + \lambda_{ij}(\sigma_j - \sigma_1) \qquad (9)$$

We also derive estimands that compare the average net farm income of complete adoption with partial adoptions. This is the average adoption effect of a complete package of CSA practices conditional on complete adopters (ATT_P), and answers the question of how the average net farm income would change if everyone who adopted a combination of all CSA practices had instead adopt only some of the practices. This is computed as follows:

$$ATT_P = (Q_{i16} \mid I_i = 16) - E(Q_{ij} \mid I_i = j) = Z_{i16}(\delta_{16} - \delta_j) + \lambda_{i16}(\sigma_{16} - \sigma_j) \quad \text{for } j= 2, \ldots, 15 \qquad (10)$$

4. Results and Discussion

4.1 Factors Influencing Adoption Decisions

The estimation results from the MVP model with Mundlak's method are reported in Table 5. The model is estimated using the maximum likelihood method on plot-level observations. We test the null hypothesis that all regression coefficients in the four adoption equations are jointly equal to zero. The Wald statistics reject the null hypothesis and show that the model fits the data well. Similarly, the null hypothesis that all coefficients of the mean of time-varying covariates are jointly statistically equal to zero is rejected in all equations; this is in keeping with Mundlak's approach and shows the presence of correlation between unobserved household fixed effects and observed covariates.

The MVP model estimates contrast substantially across the four adoption equations, signifying the importance of separating individual adoption equations. In order to formally test this, we estimated a constrained specification with all slope coefficients forced to be equal. The likelihood ratio test statistic ($\chi^2(188)$= 4114, p=0.000) rejects the null hypothesis of equal-slope coefficients. This result indicates the heterogeneity in adoption of CSA practices and consequently supports separate analyses instead of aggregating them into one adoption variable. The null hypothesis of independence of the decisions to adopt the different CSA practices is tested by using a likelihood ratio test in which the restricted model forces off-diagonal covariance matrix terms to zero. As expected, the resulting likelihood ratio test [$\chi2(6) = 197.78$, p=0.000)] is statistically significant, indicating the rejection of the null hypothesis that the covariance of the error terms across equations are not correlated. Three of the estimated correlation coefficients (Rho) have positive signs and are statistically significant. This reveals that adoption decisions are made interdependently, i.e., that the probability of adopting a given practice is conditioned on whether or not another practice in the subset has been adopted. These results agree with earlier results of the conditional and unconditional adoption probabilities reported in Table 2. The significant cross-correlations among the practices may have an important policy implication in that factors that affect the choice of a given practice can have spillover effects on other practices as well. This reveals that the adoption decision cannot be considered as an individualized decision but rather as part of an inclusive household strategy, and therefore it should be modeled as an interdependent household decision. The results from the MVP estimation reveal that there are a large number of factors that significantly influence the adoption of the different CSA practices. There are also substantial differences in the composition of factors that affect the adoption of each of the CSA practices. The fact that there are large numbers of factors and their heterogeneity implies there is no single bullet to put forward to enhance the adoption of the available climate smart practices.

Land (total farm size in hectares), a variable depicting natural capital, is important in agricultural technology adoption models because it picks up the effect of household wealth on adoption decisions. Results from Table 4 show inconclusive results concerning the relationship between farm size and CSA practices. The land parameter is significant and positive in affecting the choice of inorganic fertilizer, which is an externally purchased modern input. The result is consistent with the notion that, under climate change, where risk and uncertainty are more prevalent, wealthier farmers are abler to undertake risk and thus more willing to use those modern inputs. On the other hand, the inverse relationship between farm size and use of cropping system diversification suggests that, under climate change, small land size can induce diversification that favors intensification in the system, such that improved soil fertility and water holding capacity increases yields and resilience to climate change. This result is consistent with earlier works by Teklewold et al. (2019) and Kassie et al. (2015) in Ethiopia. The result also suggests that cropping system diversification is pro-poor, in that rural households who are unable to afford purchased external farm inputs may be able to take advantage of these systems.

Off-farm participation, remittance and household assets positively influence the probability of choice of modern seeds, revealing the role of liquidity constraints in the adoption of capital-intensive inputs. The size of livestock holdings (in terms of TLU) is also a measure of household's wealth that may relax the financial constraints on the purchase of inorganic fertilizer. Livestock is also a source of manure, the major component of organic fertilizer.

Our results indicate statistically significant and positive correlation between the fertilizer subsidy variable and adoption of inorganic and organic fertilizer. This result seems to imply that participation in the fertilizer subsidy program results in a crowding-in effect of these complementary soil fertility management practices; in other words, the use of inorganic fertilizer does not crowd out organic fertilizer. The result is consistent with Marenya and Barrett (2009) in Kenya, which suggests the role of fertilizer subsidy as a means of creating a synergistic relationship in providing organic and inorganic matter to the soil.

Households who possess and use a mobile telephone are more likely to use organic fertilizer. This implies that availability of communication infrastructure and access to information related to markets and production is key to enhancing the use of climate change adaptation practices. However, it is worthwhile to note that ownership of a mobile phone may also be picking up a wealth or liquidity effect in the sense that those who own a mobile may also have more cash income to finance the purchase of technologies.

By contrast, there is a negative effect of internet use on the choice of CSA practices. This may imply the limited role of internet access in the technology adoption process.

Spatial distance to markets has a negative and significant effect on the choice of cropping system diversification, modern seeds and inorganic fertilizer. This is probably because distance increases the transaction costs to the market.

The results also provide empirical evidence on the importance of climate variables in determining the choice of combination of CSA practices. We included the location dummy variable (at agro-ecological zone level) to account for possible heterogeneity in climatic situations, institutional service provision and other factors influencing adaptation strategies. The MVP result indicates significant differences across locations for each CSA strategy, suggesting CSA practices are location specific. Along these lines, the results further highlight the importance of rainfall and plot-level shocks in determining the adoption of CSA practices. The result shows that in areas and years which have pest shocks or climatic shocks, such as timing, amount and distribution of rainfall and temperature, it is more likely that the household shifts from mono-cropping to more climate-smart agricultural practices such as cropping system diversification. This finding suggests that smallholder farmers who experience climate shock and pest incidence are using cropping system diversification as an adaptation strategy to mitigate these risks.

The results also underline the significance of land tenure security and farm characteristics for the choice of CSA practices. As expected, the decision to use cropping system diversification and organic fertilizer is more likely on more fragmented plots. This is perhaps related to the transaction costs associated with management of the fragmented plots, particularly in transporting inputs and the difficulty of monitoring (Teklewold et al., 2013). We also found that land tenure influences the decision to apply improved crop seeds and organic fertilizer, which are more common on owner-cultivated plots than on rented in plots. The result is consistent with our expectation and also in agreement with previous related work in Ethiopia by Kassie et al. (2015). Given the fact that the adoption of organic fertilizer contribute to crop growth in other ways in addition to supplying nutrients (Fairhurst, 2012), this inter-temporal aspect suggests that secure land tenure will positively impact adaptation decisions. Conversely, a lack of clear tenure rights removes incentives to make the typically long-run investments that maintain land in such a way that it is resilient to climate change (IFAD 2012). Finally, other bio-physical plot characteristics also condition the adoption decisions, suggesting the importance of considering these characteristics in promoting different types of CSA practices.

4.2 Effects of Adoption

The results of adoption of multiple CSA practices are presented in Table 6. To determine the average effects of adoption of various combinations of CSA practices on farm income, net farm income is compared to what it would have been if they had not adopted the practices. These are obtained through equations (5) and (7). The results are shown in Table 6, where columns A and B respectively present the actual net farm income and counterfactual outcomes. Column C presents the average adoption net farm effects (ATT), computed as the difference between the above respective columns. The results reveal heterogeneity in the differences in income due to adoption of CSA practices and imply differences in returns to resources.

In general, the results show that the adoption of any of the CSA practices provides higher net farm income compared with non-adoption (Table 6). The positive income effect is observed irrespective of whether the practices are adopted in isolation or in combination. In all counterfactual cases, farm households who actually adopted the given CSA practices would have obtained lower farm income if they had not adopted. The results highlight that, in spite of some heterogeneity in the effects depending on the type of CSA practices, the joint adoption of multiple CSA practices provides higher farm income compared with adoption of CSA practices individually. The gain in farm income from shifting from adoption of any of the individual CSA practices to all four practices is higher than the gain from shifting from one to two or three practices. The result is consistent with Teklewold et al. (2013) in Ethiopia, who found that adoption of a package of sustainable agricultural practices provides higher economic gains than individual or non-adoption.

The net farm income gains from adopting organic fertilizer, improved seeds, or cropping system diversification individually range from 7.2 to 8.2 thousand Naira[4]/ha. This is higher than the net farm income from non-adoption. Compared with the gain from adoption of individual practices, we found a potential additional gain of more than 45% of net farm income from adopting a combination of three of the above CSA practices. Similarly, the net farm income further increases to 21.2 thousand Naira/ha from complete adoption of all four practices. Figure 2 shows the net farm income effect of partial versus complete adoption. The result indicates an increase of farm returns with increasing the number of practices adopted. We found that, in general, farm income from adoption of the combination of all four CSA practices is significantly higher compared with farm income with partial adoption. In all counterfactual cases, farm households who actually adopted all four practices would have obtained significantly lower farm income if fewer practices were adopted. That is, the adoption gap in farm returns widens as the number of practices adopted decreases. The potential additional gains of farm income from complete adoption ranges from 6 to 8 thousand Naira/ha relative to the case if adopters of all practices had instead adopted any practice. Similarly, the adoption effects further widen in the range of 12 to 13 thousands Naira/ha if adopters of all practices had instead adopted any two practices and from 12 to 27 thousand Naira/ha if they had adopted only one of the CSA practices[5]. This shows the synergistic relationship and positive effects of adoption intensity on farm income. The result agrees with Teklewold et al. (2019) in Ethiopia, who found a complementary relationship with a possible synergy among adaptation practices that could lead to co-benefits. The result also shows that this is an important incentive for farmers to apply multiple adaptation practices, confirming the argument that the extent to which the impacts of climate change are felt depends in large part on the extent of adaptation (Gbetibouo, 2009).

5. Conclusion

The objectives of this paper are to understand the incentives and constraints affecting households' decisions to adopt multiple CSA – cropping system diversification, modern seeds, inorganic and organic fertilizer – either separately or jointly, and to investigate the impacts of adoption of a combination of these practices on net farm income. We developed a two-stage endogenous switching regression method using nationally representative panel household- and plot-level data sets coupled with spatial climate data in rural Nigeria. The method corrects for

[4] The current exchange rate is 1 USD=411 Nigerian naira.
[5] See Annex 1 for the statistics.

selection bias in adoption because the same unobserved factors (motivations and skills) that lead some farmers to adopt CSA practices might enable them to change their farm returns even without adjusting their adoptions. Our approach extends the existing body of knowledge by allowing for correlations across the CSA practices and by considering the impact of a combination of externally purchased intensification inputs (inorganic fertilizer and modern seeds) and knowledge-intensive and resource-conserving sustainable practices (cropping system diversification and organic fertilizer).

Coefficient estimates of the multivariate probit model revealed that the likelihood of adoption of CSA practices is influenced by plot, household and agro-ecological characteristics. These include plot-level shocks, soil characteristics, market access, wealth, and demographic characteristics. This analysis of the role of these variables in determining the choice of a portfolio of practices can be used to design policies that enhance the climate change adaptation possibilities among farmers. For instance, the significance of tenure security in influencing the probability of adoption of CSA practices calls attention to the importance of securing property rights as an incentive in climate change adaptation. The significant relationship between agro-ecological zones and adoption of CSA practices implies the need for careful design and targeting of agro-ecological based combination of CSA strategies.

The following conclusions can be derived. First, adoption of individual CSAs increases income compared with non-adoption. Second, adoption of multiple CSAs provides higher farm returns than adoption of individual practices. Third, the highest farm income was achieved when farmers adopted all practices jointly, rather than partial adoption.

The results highlight that there is a complementarity between CSA practices in terms of adoption and in their synergistic effect to enhance farm income. This correlation among the CSA practices may have important policy implication in that adaptation options shouldn’t be considered independently and policy options should tailor packages of adaptation practices to specific areas. This result also suggests that policymakers should explicitly design strategies that enhance the adoption of externally purchased technological farm inputs jointly with the locally available knowledge-intensive land management options.

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Table 1. The unconditional choice of the different climate smart agricultural (CSA) strategies

	Wave			
	2011	2013	2016	All
Cropping system diversification (C)	81.65	83.33	80.00	81.66
Improved seeds (V)	72.04	78.58	53.78	67.99
Inorganic fertilizer (F)	38.78	37.73	41.90	39.50
Organic fertilizer (O)	7.65	5.34	29.19	14.28

Table 2. Binary triplets characterizing the joint and marginal probabilities of choice of climate smart agricultural strategies: Cropping system diversification (C), Inorganic fertilizer (F), Organic fertilizer (O) and Improved seeds (V), %.

Choice (j)	Combination of strategies (j)	Definition	Joint probability
1	$(I_C = 0, I_V = 0, I_F = 0, I_O = 0)$	None	5.42
2	$(I_C = 0, I_V = 0, I_F = 0, I_O = 1)$	Organic fertilizer only	0.38
3	$(I_C = 0, I_V = 0, I_F = 1, I_O = 0)$	Inorganic fertilizer only	2.23
4	$(I_C = 0, I_V = 1, I_F = 0, I_O = 0)$	Improved seed only	7.13
5	$(I_C = 1, I_V = 0, I_F = 0, I_O = 0)$	Cropping system diversification only	16.73
6	$(I_C = 0, I_V = 0, I_F = 1, I_O = 1)$	Inorganic & organic fertilizer	0.39
7	$(I_C = 0, I_V = 1, I_F = 0, I_O = 1)$	Improved seed & organic fertilizer	0.19
8	$(I_C = 1, I_V = 0, I_F = 0, I_O = 1)$	Cropping system diversification & organic fertilizer	4.41
9	$(I_C = 0, I_V = 1, I_F = 1, I_O = 0)$	Improved seed & inorganic fertilizer	3.04
10	$(I_C = 1, I_V = 0, I_F = 1, I_O = 0)$	Cropping system diversification & inorganic fertilizer	11.29
11	$(I_C = 1, I_V = 1, I_F = 0, I_O = 0)$	Cropping system diversification & improved seed	24.87
12	$(I_C = 0, I_V = 1, I_F = 1, I_O = 1)$	Improved seed, inorganic & organic fertilizer	0.09
13	$(I_C = 1, I_V = 0, I_F = 1, I_O = 1)$	Cropping system diversification, inorganic & organic fertilizer	4.74
14	$(I_C = 1, I_V = 1, I_F = 0, I_O = 1)$	Cropping system diversification, improved seed & organic fertilizer	1.76
15	$(I_C = 1, I_V = 1, I_F = 1, I_O = 0)$	Cropping system diversification, improved seed & inorganic fertilizer	16.27
16	$(I_C = 1, I_V = 1, I_F = 1, I_O = 1)$	Cropping system diversification, improved seed, inorganic & organic fertilizer	1.04

Note: A ‘1’ indicates that the CSA practice is adopted, while a ‘0’ indicates that the practice is not adopted.

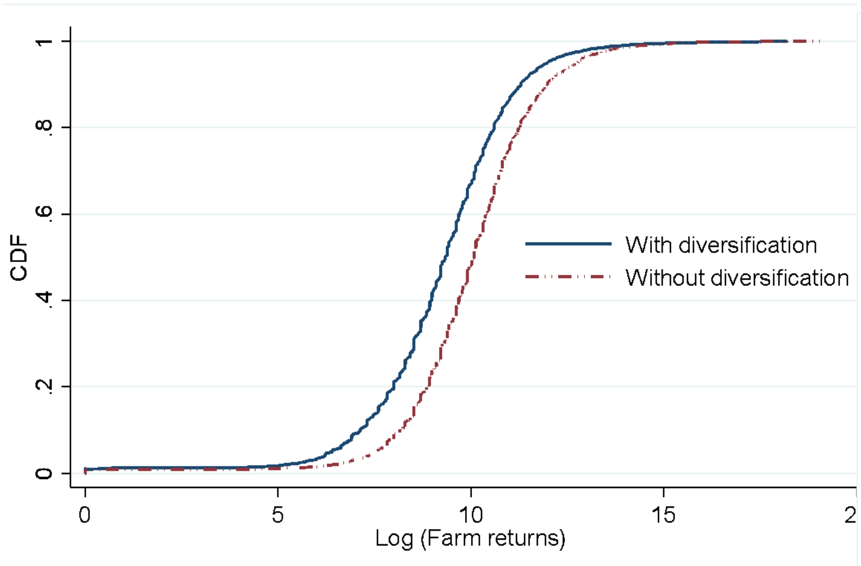
Table 3. The unconditional and conditional choice of the different coping strategies

	CSA strategies			
	C	V	F	O
$P(I_k = 1)$	81.66	67.99	39.50	14.28
$P(I_k = 1 \vert I_C = 1)$	100.00	68.15	41.19	15.79
$P(I_k = 1 \vert I_V = 1)$	81.85	100.00	39.44	13.53
$P(I_k = 1 \vert I_F = 1)$	85.18	67.89	100.00	19.71
$P(I_k = 1 \vert I_O = 1)$	90.34	64.45	54.52	100.00
$P(I_k = 1 \vert I_F = 1 \;\&\; I_O = 1)$	92.38	18.12	100.00	100.00
$P(I_k = 1 \vert I_V = 1 \;\&\; I_O = 1)$	91.02	100.00	36.79	100.00
$P(I_k = 1 \vert I_V = 1 \;\&\; I_F = 1)$	84.68	100.00	100.00	5.55
$P(I_k = 1 \vert I_C = 1 \;\&\; I_O = 1)$	100.00	23.47	48.38	100.00
$P(I_k = 1 \vert I_C = 1 \;\&\; I_F = 1)$	100.00	51.92	100.00	17.36
$P(I_k = 1 \vert I_C = 1 \;\&\; I_V = 1)$	100.00	100.00	39.39	6.39
$P(I_k = 1 \vert I_V = 1 \;\&\; I_F = 1 \;\&\; I_O = 1)$	92.12	100.00	100.00	100.00
$P(I_k = 1 \vert I_C = 1 \;\&\; I_F = 1 \;\&\; I_O = 1)$	100.00	18.03	100.00	100.00
$P(I_k = 1 \vert I_C = 1 \;\&\; I_V = 1 \;\&\; I_O = 1)$	100.00	100.00	37.17	100.00
$P(I_k = 1 \vert I_C = 1 \;\&\; I_V = 1 \;\&\; I_F = 1)$	100.00	100.00	100.00	6.03

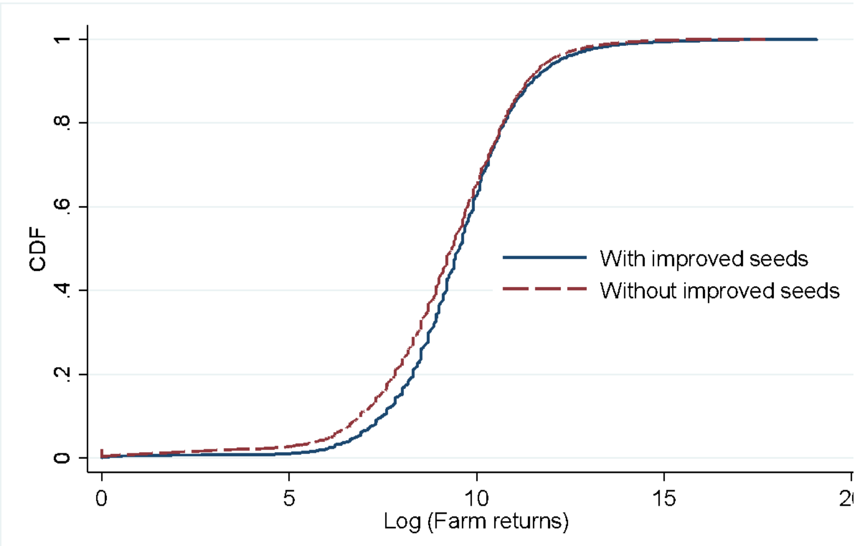
I_k is a binary variable representing the adoption status with respect to CSA strategies k (k = C, V, F & O).

Table 4. Description and summary statistics of the variables used in the empirical estimation

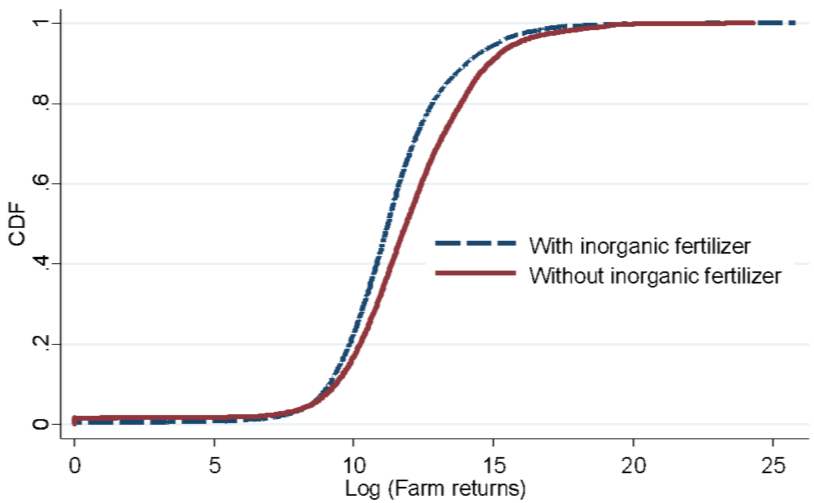
				Adoption status							
		All samples		Cropping system diversification		Improved seeds		Inorganic fertilizer		Organic fertilizer	
Variable	Description	Mean	Std, Dev	Mean	Std, Dev	Mean	Std, Dev	Mean	Std, Dev	Mean	Std, Dev
Dependent variable:	Farm return, (‘000 NAIRA/ha)	84.55	101.39	81.04	98.84	85.74	106.34	77.27	69.26	67.79	49.69
Household features											
HH_Sex	1=if male headed household	0.87	0.34	0.87	0.34	0.88	0.33	0.92	0.28	0.91	0.28
HH_Age	Age of the household head, yrs	37.58	27.11	37.93	27.36	36.57	27.26	36.34	26.17	44.50	23.38
Married	1=if household head is married	0.83	0.38	0.83	0.38	0.84	0.37	0.89	0.31	0.89	0.31
Educlevel	Education level of the head, yrs	10.00	13.98	10.09	14.06	8.88	12.76	11.78	15.61	14.06	17.56
HHsize	Number of household member	6.88	3.38	6.79	3.35	6.88	3.33	7.54	3.46	7.71	3.45
Wealth											
Farmsize	Farm size, ha	9.34	178.63	8.44	161.94	6.46	96.35	16.02	269.21	8.37	127.46
Offarm	1=if participated in off-farm activities	0.19	0.39	0.19	0.39	0.20	0.40	0.18	0.39	0.14	0.34
Asset	Asset value (’000 NAIRA)	96.09	1037.50	97.37	1131.79	97.06	975.33	79.01	319.63	85.74	657.59
TLU	Tropical livestock unit	1.79	28.73	1.78	31.50	1.64	18.11	2.53	44.84	3.43	53.02
Remittance	1=if household received remittances	0.03	0.16	0.03	0.17	0.03	0.16	0.03	0.18	0.04	0.19
Fertsubsdy	1=if recieved fertilizer subsidy	0.01	0.12	0.02	0.13	0.01	0.12	0.03	0.16	0.04	0.20
Credit	1=if borrowed money	0.18	0.38	0.18	0.39	0.21	0.40	0.18	0.39	0.11	0.31
Access to information											
Dist_road	Distance to main road, km	9.70	11.28	9.65	11.18	10.08	11.52	10.42	12.06	9.41	11.18
Dist_market	Distance to main market, km	70.01	37.03	67.77	35.46	70.14	36.81	61.87	32.39	61.06	31.59
Extension	1=if access to extension services	0.13	0.34	0.13	0.34	0.12	0.32	0.18	0.38	0.19	0.39
Mobile	1=if own mobile	0.71	0.45	0.71	0.45	0.69	0.46	0.73	0.45	0.83	0.38
Internet	1=if access to internet services	0.15	0.35	0.15	0.35	0.14	0.35	0.13	0.34	0.09	0.29
Shock											
Healthshock	1=if the household faces health (illness/death) shock	0.15	0.36	0.15	0.36	0.15	0.36	0.14	0.34	0.11	0.32
Climatshock	1=if the household faces climate shock	0.11	0.31	0.11	0.31	0.11	0.32	0.13	0.34	0.10	0.30
Pestshock	1=if the household faces pest attack shock	0.02	0.13	0.02	0.13	0.02	0.13	0.02	0.13	0.01	0.11
Farm features											
Numbparcel	Number of parcels	5.46	2.87	5.79	2.88	5.45	2.86	5.39	2.82	5.69	2.88
Tenure	1=if own the plots	0.86	0.35	0.86	0.35	0.86	0.34	0.85	0.36	0.82	0.38
Plotdist	Distance from house to plots, km	2.45	25.79	2.37	25.79	2.41	25.21	2.48	25.99	1.43	17.57
Plotslop	Slope of the plot, %	2.97	2.77	2.95	2.73	2.90	2.67	2.58	2.31	2.22	1.66
Plotelevaton	Elevation of the plot, m	300.88	201.71	302.80	199.11	300.41	203.79	375.25	230.10	381.69	176.72
Plotwetness	Plot potential wetness index	14.55	2.74	14.53	2.66	14.57	2.75	14.67	2.66	14.89	2.82
Climate											
Temprature	Mean daily temperature, 0C	26.33	0.96	26.32	0.94	26.35	0.99	26.18	1.16	26.32	0.98
Precipitation	Mean annual rainfall, mm	1418.89	593.23	1419.94	596.75	1410.70	592.09	1234.23	553.06	1113.56	580.23
Semiarid	1= if Tropic-warm/semiarid agro-ecological zone	0.35	0.48	0.36	0.48	0.35	0.48	0.54	0.50	0.67	0.47
Subhumid	1= if Tropic-warm/subhumid agro-ecological zone	0.57	0.50	0.56	0.50	0.56	0.50	0.39	0.49	0.28	0.45
Humid	1= if Tropic-warm/humid agro-ecological zone	0.07	0.26	0.07	0.25	0.07	0.26	0.04	0.21	0.05	0.21
	Number of observation	34,145		27,882		23,215		13,486		4,875	



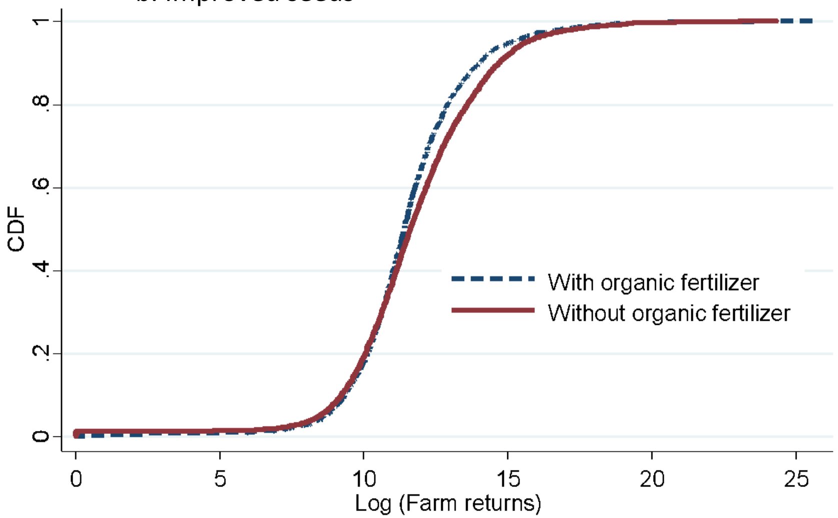
a. Cropping system diversification



b. Improved seeds



c. Inorganic fertilizer



d. Organic fertilizer

Fig 1. Cumulative distribution for the impact of adaptation practices on farm net income

Table 5. Parameter estimates of the multivariate probit model with Mundlak approach – choice of CSA strategies

Variables	Cropping system diversification (C) Coefficient	Standard Error	Improved seeds (V) Coefficient	Standard Error	Inorganic fertilizer (F) Coefficient	Standard Error	Organic fertilizer (O) Coefficient	Standard Error
Household features								
HH_Sex	0.056	0.080	0.128*	0.073	-0.178*	0.096	-0.092	0.157
HH_Age	0.002*	0.001	-0.000	0.001	-0.007***	0.002	0.000	0.002
Married	-0.061	0.070	-0.045	0.065	0.254***	0.084	0.073	0.144
Educlevel	0.002*	0.001	-0.007***	0.001	0.005***	0.001	0.000	0.001
HHsize	-0.005	0.014	-0.029	0.020	0.007	0.019	0.026	0.026
Wealth								
Farmsize	-0.0001**	0.0001	-0.0001	0.0001	0.0001***	0.0001	-0.0001	0.0001
Offarm	-0.007	0.041	0.078*	0.046	-0.054	0.051	-0.084	0.079
Asset	-0.0001*	0.0001	0.0001**	0.00001	-0.0001	0.0001	-0.0001	0.000
TLU	0.002	0.001	-0.002	0.002	0.006**	0.003	0.001***	0.000
Remittance	0.079	0.136	0.297**	0.124	0.221	0.154	0.044	0.197
Fertsubsdy	-0.033	0.126	-0.029	0.139	0.448***	0.135	0.808***	0.146
Credit	0.102**	0.040	0.218***	0.040	0.073*	0.044	0.087	0.063
Access to information								
Dist_road	0.001	0.001	0.003*	0.001	0.001	0.002	-0.001	0.002
Dist_market	-0.003***	0.000	0.000	0.000	-0.006***	0.001	-0.003***	0.001
Extension	0.179***	0.049	-0.202***	0.042	0.231***	0.049	-0.006	0.061
Mobile	-0.030	0.032	0.044	0.042	0.054	0.044	0.209***	0.067
Internet	-0.130***	0.042	-0.141***	0.054	-0.109**	0.054	-0.296***	0.092
Shock								
Healthshock	-0.015	0.044	-0.075	0.055	-0.060	0.052	-0.057	0.083
Climatshock	0.064*	0.025	-0.063	0.064	-0.024	0.062	-0.087	0.091
Pestshock	0.272**	0.122	-0.138	0.146	-0.089	0.132	-0.256	0.244
Farm features								
Numbparcel	0.165***	0.011	-0.004	0.006	0.006	0.008	0.050***	0.009
Tenure	-0.013	0.040	0.084**	0.037	-0.089	0.046	-0.368***	0.056
Plotdist	-0.000	0.000	-0.000	0.000	-0.000	0.000	-0.001	0.001
Plotslop	-0.002	0.005	-0.014***	0.004	-0.029***	0.006	-0.044***	0.010
Plotelevaton	0.0001	0.0001	-0.000*	0.000	0.002***	0.0001	0.001***	0.000
Plotwetness	-0.009*	0.004	-0.003	0.005	-0.010*	0.005	-0.004	0.008
Climate								
Temprature	-0.377***	0.142	-0.274	0.229	-0.011	0.115	-0.170	0.290
Precipitation	-0.000	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Semiarid	0.950***	0.156	-0.702***	0.138	-0.328	0.277	0.596**	0.256
Subhumid	0.339**	0.155	-0.727***	0.141	-0.886***	0.279	-0.065	0.265
Humid	-0.247	0.176	-0.628***	0.160	-1.181***	0.315	0.212	0.298
Wave								
Year – 2011	0.177**	0.076	0.419***	0.076	-0.391***	0.090	-0.881***	0.114
Year – 2013	0.121***	0.040	0.586***	0.046	-0.059	0.046	-1.110***	0.067
Constant	-0.224	0.782	0.224	0.708	-1.757*	0.940	-6.253***	1.357
RHO:								
Organic fertilizer	0.154***	0.020	0.062***	0.023	0.028	0.027		
Inorganic fertilizer	0.073***	0.018	0.009	0.017				
Improved seeds	0.012	0.015						
Joint significance of time varying variables, $\chi^2(8)$	78.10***		20.54*		13.74		20.80*	
Observations			34145					
Model chi-square			Wald $\chi^2(188) = 34145$; Prob > $\chi^2 = 0.000$					
Likelihood ratio test $RHO_{C,V} = RHO_{C,F} = RHO_{C,O} = RHO_{V,F} = RHO_{V,O} = RHO_{F,O} = \chi^2(6) = 197.78$; Prob > $\chi^2 = 0.000$								

Note: ***, ** and * denote significance at 1%, 5% and 10%. All regressions include household time average variables. Robust clustered standard errors at the household level.

Table 6. Average expected farm return outcome with adoption on different CSA strategies

Strategies	Actual farm return if household did adopt (A)		Counterfactual farm return if household didn't adopt (B)		Adoption Effects (C)	
Organic fertilizer only	54460.27	(204.50)	46175.37	(2953.27)	8284.90	(2960.34)***
Inorganic fertilizer only	38247.75	(6476.64)	37358.63	(2562.69)	889.12	(6965.22)
Improved seed only	40684.86	(789.03)	33456.80	(584.80)	7228.06	(982.12)***
Cropping system diversification only	42836.86	(650.87)	34880.44	(412.78)	7956.42	(770.72)***
Cropping system diversification & organic fertilizer	66891.69	(2858.63)	50172.85	(847.25)	16718.84	(2981.54)***
Improved seed & inorganic fertilizer	48647.74	(873.56)	33099.62	(974.94)	15548.12	(1309.05)***
Cropping system diversification & inorganic fertilizer	49906.52	(530.86)	41185.66	(898.16)	8720.86	(1043.31)***
Cropping system diversification & improved seed	49043.15	(313.29)	33535.99	(252.73)	15507.16	(402.52)***
Cropping system diversification, inorganic & organic fertilizer	61303.03	(83.18)	45417.25	(1035.00)	15885.78	(1038.33)***
Cropping system diversification, improved seed & organic fertilizer	61895.69	(1484.04)	46988.48	(671.92)	14907.21	(1629.07)***
Cropping system diversification, improved seed & inorganic fertilizer	55059.46	(513.01)	38994.90	(310.20)	16064.56	(599.50)***
Cropping system diversification, improved seed, inorganic & organic fertilizer	68122.19	(1345.19)	46949.75	(753.52)	21172.44	(1541.86)***

Note: Numbers in parentheses are standard errors; *. ** and *** indicate statistical significance at 10%, 5% and 1% level, respectively.

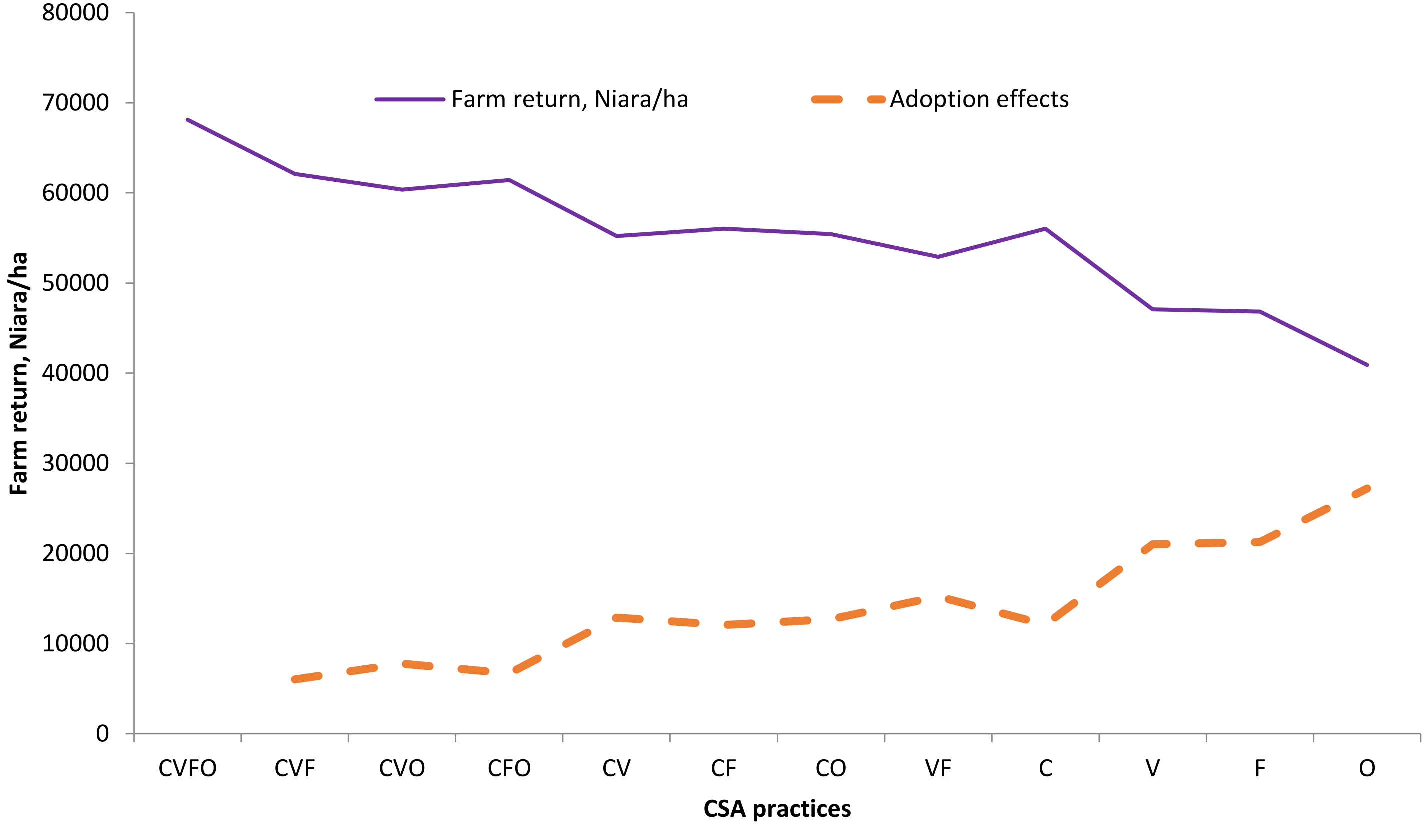


Figure 2. Expected farm return and adoption effects of different CSA strategies conditional on complete adoption

Annex 1. Average treatment effects of the treated - expected farm return effects of adoption on different CSA strategies conditional on complete adoption

Strategies	Farm returns		Adoption Effects	
Cropping system diversification, improved seed, inorganic & organic fertilizer	68122.19	(1345.19)		
Cropping system diversification, improved seed & inorganic fertilizer	62092.09	(1326.68)	6030.10	(1889.34)***
Cropping system diversification, improved seed & organic fertilizer	60352.56	(1444.22)	7769.63	(1973.65)***
Cropping system diversification, inorganic & organic fertilizer	61415.66	(46.99)	6706.53	(1346.01)***
Cropping system diversification & improved seed	55227.50	(1144.36)	12894.69	(1766.10)***
Cropping system diversification & inorganic fertilizer	56044.96	(821.97)	12077.23	(1576.44)***
Improved seed & inorganic fertilizer	52908.60	(1023.22)	15213.59	(1690.13)***
Cropping system diversification & organic fertilizer	55424.31	(17105.14)	12697.88	(17157.95)
Cropping system diversification only	56024.48	(850.69)	12097.71	(1591.61)***
Improved seed only	47100.01	(731.96)	21022.18	(1531.44)***
Inorganic fertilizer only	46846.81	(1327.08)	21275.38	(1889.62)***
Organic fertilizer only	40917.44	(24.94)	27204.75	(1345.42)***

Note: Numbers in parentheses are standard errors; *. ** and *** indicate statistical significance at 10%. 5% and 1% level, respectively