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Adoption of climate-smart practices and its impact on farm performance and risk exposure among smallholder farmers in Ghana

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Increased climate variability during the last four decades has made the agricultural environment in many developing countries more uncertain, resulting in increasing exposure to risk when producing crops. In this study, we use recent farm-level data from Ghana to examine the drivers of individual and joint adoption of crop choice and soil and water conservation practices, and how adoption of these practices impacts on farm performance (crop revenue) and exposure to risks (skewness of crop yield). We employ a multinomial endogenous switching regression model to account for selectivity bias due to both observable and unobservable factors. The empirical results reveal that farmers' adoption of crop choice and soil and water conservation leads to higher crop revenues and reduced riskiness in crop production, with the largest impact on crop revenues coming from joint adoption. The findings also show that education of the household head, access to extension and weather information influence the likelihood of adopting these practices. Thus, enhancing extension services and access to climate information and irrigation can reduce gaps in adoption of soil and water conservation and crop choice, considered as climate-smart practices that will eventually improve crop revenues and reduce farmers' exposure to climate-related production risks.

Key words: Africa, climate-smart practices, farm performance, impact assessment, risk exposure.

1. Introduction

Climate variability continues to be a major challenge to achieving food security in sub-Saharan Africa (SSA) due to the incidence of high temperature, erratic rainfall regimes, coupled with low adoption of modern technologies (IPCC 2007; World Bank 2010). Although sub-Saharan Africa contributes less than 5 per cent of global greenhouse gas (GHG) emissions, it is the most vulnerable to the negative effects of climate change, as the region's development prospects are closely linked to climate because of heavy reliance on rainfall (IAASTD 2009; Tol 2018). The vulnerability has been attributed to structural, technological and institutional weaknesses, higher poverty, as well as relative proximity to the equator (IPCC 2007). The impact of climate change on agricultural productivity especially in developing countries is well

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documented (IPCC 2007; Di Falco and Veronesi 2013; Gunathilaka *et al.* 2018). The key issue is not whether climate change will have adverse impact on crop productivity, but the extent of productivity losses from climate variability or uncertainties and the prospect of mitigating the negative impacts through adoption of appropriate climate-smart practices.

The international community has recommended the incorporation of adaptation into national development plans (IPCC 2007; World Bank 2010). A better understanding of adaptation is critical, especially in developing countries and in the agricultural sector, because of their vulnerability to climate change (IPCC 2007; Tibesigwa*et al.* 2014). As argued by Tol (2018), adaptation is being considered by economists more widely as part of important measures to complement climate mitigation. Various climate-smart practices, including planting of new crop varieties, changing planting dates, growing drought-resistant crops, use of crop insurance mechanisms, irrigation, and adoption of soil and water conservation measures, have been used by farmers in developing countries to cope with the negative effects of climate change and to ensure high yields (Di Falco and Veronesi 2013; Adamson *et al.* 2017). Thus, a practice may be considered as 'climate-smart', if it falls within the three main objectives of climate-smart agriculture, stated by the FAO (2013) as: (a) sustainably increasing agricultural productivity and incomes; (b) adapting and building resilience to climate change; and (c) reducing greenhouse gas emissions.

Although the promotion of climate-smart agriculture in sub-Saharan Africa is ongoing as part of many developing countries' sustainable agricultural development policy (Lipper and Zilberman 2018), empirical evidence shows that adoption rates among smallholder farmers are still low (Arslan *et al.* 2015; Barnard *et al.* 2015). Promotion of climate-smart agriculture in Ghana gained momentum since the country ratified the United Nations Framework Convention on Climate Change in 1995 (EPA 2011). The Kyoto Protocol was adopted by Ghana's Parliament in 2002 and eventually led to the current National Climate Change Policy (Ministry of Environment, Science, Technology and Innovation 2015). Through various state and non-state agencies, Ghana has sought to make climate-smart agriculture part of its agricultural development policy (MoFA 2018).

There exists extensive literature on adoption impacts of individual climate-smart practices, with divergent findings (e.g. Di Falco and Chavas 2009; Kato *et al.* 2011; Di Falco and Veronesi 2013; Abdulai and Huffman 2014; Zougmore *et al.* 2014; Ng'ombe *et al.* 2017). Among the frequently mentioned pathways include climate-smart agriculture's ability to increase crop yields, food and nutrition security, reduction in crop failure (e.g., Kato *et al.* 2011; Di Falco and Veronesi 2013; Abdulai and Huffman 2014). Other studies report lower farm returns from plots treated with certain soil conservations practices (e.g. stone bunds) in Burkina Faso (World Bank 2009), while Nkala *et al.* (2011) find no significant effect of minimum tillage on household incomes in Mozambique.

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Furthermore, Di Falco and Chavas (2009) find a positive effect of biodiversity on risk reduction among barley farms in Ethiopia. The study by Di Falco and Veronesi (2013) also indicates that adaptation to climate change, through adoption of soil conservation, changing crop varieties, switching from early to late planting and other measures, led to increased yield of maize among farm households in Ethiopia. Other studies have indicated that soil conservation, crop choice and other practices can increase technical efficiencies among farmers, as well as minimise on-farm environmental damage (Solis *et al.* 2007; Veettil *et al.* 2017; Sabiha *et al.* 2017). Although these studies contribute towards the understanding of the factors driving the adoption of climate-smart practice and impacts on productivity and risk exposure, there is a gap in the literature about the potential complementarity or substitutability among individual and combined climate-smart practices. In addition, the mixed findings from these studies about adoption impacts on farm performance also provide motivation for further empirical investigation into the potential impacts of specific climate-smart agricultural practices on crop revenues and production risk exposure, with respect to agroecology.

A few studies have evaluated adoption and impacts of multiple climate-smart practices on smallholder farmers' productivity and risk exposure, usually from a monocropping perspective (e.g. maize, rice or wheat) (e.g. Di Falco and Veronesi 2013; Kassie *et al.* 2014; Ng'ombe *et al.* 2017). However, this approach of analysing farm productivity and risk from a monocropping perspective might under-estimate or over-estimate the true impacts of adoption for a number of reasons. First, implementation of climate-smart practices, like soil and water conservation in a mixed cropping setting, might offer benefits to other crops including maize or sorghum, which could not be captured if the analyst considered only maize yield and excluded other crops. Second, there may also be negative interaction among crops in a mixed-crop setting, where only yield of one crop increases at the expense of others. Analysing the benefits of conservation agriculture on productivity of farms in a mixed-crop setting, Tessema *et al.* (2015) observed that some crops enhance the productivity of others. For instance, in maize–cowpea mixed cropping, maize yields could be enhanced due to atmospheric nitrogen fixation by cowpea. Hence, it is prudent to analyse productivity by capturing outputs of all crops rather than that of a single crop.

In this study, we examine joint adoption of climate-smart agricultural practices and how adoption impacts on crop revenues and exposure to production risk among mixed-crop farmers in Ghana. We define climate-smart practice more broadly to include crop choice and soil and water conservation measures (FAO 2013). Crop choice as climate-smart agricultural practice is defined to include the use of modern varieties, drought-resistant and early maturing varieties that enable crop farmers to cope with erratic rainfall or short rainfall season. It also captures changing crops in response to climate variability, particularly rainfall. A number of studies have linked adoption of crop choice/switching crops and planting dates to farmers'

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climate change adaptation behaviour (e.g. Deressa *et al*. 2009; Di Falco and Veronesi 2013). It is common to intercrop cereals and other crops, especially in northern Ghana. Soil and water conservation also refers to the use of erosion control and other measures to prevent soil and nutrient loss and conserve soil moisture, such as minimum tillage, soil and stone bunds, and use of *zaï* techniques. The *zaï* technique is a soil conservation method that concentrates run-off water and organic manure in small round or square pits (Zougmore *et al*. 2014). In Ghana, it is mainly used in the dry Savannah zones, particularly in the Upper East region. Strategies that seek to minimise soil loss due to erosive rains, or reduce evaporation of water from the soil due to high temperatures, are expected to help improve crop performance (see Kato *et al*. 2011; Abdulai and Huffman 2014).

We contribute to the empirical literature by employing recent advancements in the impact assessment literature (e. g. Bourguignon *et al*. 2007; Teklewold *et al*. 2013; Wooldridge 2015), particularly the use of multinomial endogenous switching regression that enables us to account for selection bias within a multinomial setting. The approach, therefore, enables us to identify location-specific information on adoptable climate-smart practices, as well as impacts of adoption on farm performance and exposure to production risk. To the best of our knowledge, this might be the first of such studies in Ghana and among a few in sub-Saharan Africa. Specifically, we first examine the factors that affect farmers' decisions to adopt crop choice, and soil and water conservation measures, individually and jointly. Secondly, we determine the impacts of adoption on crop revenues and risk exposure among mixed-crop plots. We employ recent survey data and use a multinomial endogenous switching regression approach (Bourguignon *et al*. 2007) to achieve our research objective. Given the fact that our sample is made up of mixed-crop plots, we capture crop revenue as the value of all crops cultivated by the household on each plot (see Kato *et al*. 2011). The procedure by Antle (1983) is employed to estimate the crop revenue skewness, which is used as a proxy for downside risk or probability of crop failure. An increase in crop revenue skewness lowers the probability of crop failure, which implies a decrease in downside risk (Di Falco and Chavas 2009).

Our study is relevant to the debate on whether farmers should adopt practices individually or as a package. This study will also contribute to efforts at identifying Ghana's Nationally Determined Contributions, through which developing countries are expected to articulate their climate mitigation actions and commitment to implementation of the Paris Agreement (United Nations Framework Convention on Climate Change, 2015; MoFA 2018). To the extent that climate-smart agriculture overlap with several development goals, such as poverty reduction and food security, the empirical findings from this study can have important implications for climate policy in sub-Saharan Africa (Vale 2016; Tol 2018).

The rest of the paper is organised as follows. In the next section, we present the conceptual framework and econometric specification, as well as the

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estimation procedures. The description of the data and the variables employed in the empirical strategy are presented in Section 3. In Section 4, the empirical results are discussed, while the final section highlights the main conclusions and policy implications of the study.

2. Conceptual framework and econometric specification

We examine adoption and impacts of two climate-smart practices on farm performance. We follow previous studies (Di Falco and Chavas 2009; Kassie *et al.* 2014) and calculate crop revenue skewness distribution, that is approximated using the third central moment of crop revenue distributions. Crop revenue skewness is a good indicator of farm performance, especially under climate uncertainty because skewness captures the exposure to downside risk (Antle 1983; Di Falco and Chavas 2009). Thus, an increase in the crop revenue skewness implies a reduction in the probability of crop failure (Di Falco and Chavas 2009). Estimating the moments of crop revenues follows a sequential estimation procedure by first regressing[1] crop revenue per acre on production inputs and other farm-level variables, after which the residuals are retrieved. The third moment is calculated by raising the residual to the third power (Di Falco and Chavas 2009). The estimated third moment of crop revenue is used as outcome variables in the multinomial endogenous switching regression model to examine the impact of individual and joint adoption on risk exposure.

2.1 Modelling choice of climate-smart practice

Let us assume that the farmer's objective to use a combination of climate-smart practices is to maximise expected benefits. The i^{th} plot's expected benefit from application of a combination of practices j is represented as V^*_{ij}. However, the expected benefits captured by the latent variable V^*_{ij}, cannot be observed, but can be expressed as a function of observed characteristics (X_i), as well as unobserved factors (ε_{ij}) as:

$$V^*_{ij} = X_{ij}\beta_j + \theta_j\overline{X}_{ij} + \varepsilon_{ij} \tag{1}$$

For the adoption decision, let V_i denote an index that indicates the farmer's observed choice of a combination of practices, such that:

$$V_i = \begin{cases} 1 \text{ iff } V^*_{i1} > \max\limits_{k\neq 1}(V^*_{ik}) \text{ or } \varepsilon_{i1} < 0 \\ \quad \vdots \qquad\qquad \vdots \qquad\qquad \vdots \\ M \text{ iff } V^*_{iM} > \max\limits_{k\neq j}(V^*_{ij}) \text{or } \varepsilon_{iM} < 0 \end{cases} \tag{2}$$

where $\max\limits_{k\neq j}(V^*_{ik} - V^*_{ij}) < 0$. Equation 2 indicates that a farmer will apply climate-smart practice j on plot i to maximise expected benefit, if the chosen

[1] The OLS estimates of the crop revenue function are not reported in this paper to save space.

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practice provides greater expected benefit than any other alternative option $k \neq j$, that is if $\varepsilon_{ij} = \max_{k \neq j} (V_{ik}^* - V_{ij}^*) < 0, \forall j, k \in M$.

In this study, the adoption of two climate-smart practices, crop choice, and soil and water conservation, results in four possible combinations from which the farmer can choose (namely: crop choice only; soil and water conservation only; joint adoption; or non-adoption).

Assuming that ε_{ij} in Equation 1 is independently and identically Gumbel distributed, the probability that practice j will be chosen can be specified by a multinomial logit (MNL) model as (McFadden 1973).

$$P_{ij} = P(\varepsilon_{ij} < 0 | X_i) = \frac{\exp(X_{ij}\beta_j + \overline{X}_{ij}\delta_j)}{\sum_{k \neq 1}^{M} \exp(X_{ij}\beta_k + \overline{X}_{ij}\delta_k)} \tag{3}$$

where $\overline{X}_{ij}$ denotes a vector of average plot-specific variables and δ_j refers to the corresponding parameters to be estimated. The estimation of parameters of the latent model in Equation 3 is done by maximum-likelihood approach. We then model the chosen strategies within the multinomial endogenous switching regression framework (MESR) to link the climate-smart practices to the outcomes of interest, namely crop revenues and distribution of revenue skewness.

2.2 Multinomial endogenous switching regression model

The multinomial endogenous switching regression (MESR) model was proposed by Bourguignon *et al.* (2007) and has been applied in empirical studies (e.g. Di Falco and Veronesi 2013; Teklewold *et al.* 2013; Ng'ombe *et al.* 2017). We employ this approach in this study. The base category, non-adoption is indicated as j = 1. For the remaining practices (j = 2 crop choice, =3 soil and water conservation only, and j = 4 joint adoption), at least one climate-smart practice combination is applied on a plot. The outcome equation for each potential regime j is given as:

$$\begin{cases} \text{Regime } 1 : y_{i1} = Z_{i1}\alpha_1 + \overline{Z}_{i1}\theta_j + u_{i1} \text{ if } V_i = 1 \\ \qquad\qquad\qquad\qquad\qquad\quad \vdots \qquad\quad \vdots \qquad\quad \vdots \\ \text{Regime } M : y_{ij} = Z_{ij}\alpha_j + \overline{Z}_{ij}\theta_j + u_{ij} \text{ if } V_i = J \end{cases} \tag{4}$$

where y_{ij} is the outcome variable (crop revenue or risk exposure) of the i^{th} farm plot in regime M, Z_i represents a vector of farm and household characteristics, and the u's denote error terms with expected values of zero and constant variance,$\text{Var}(u_{ij}|X_i, Z_i) = \sigma_j^2$, while α_j represents a vector of parameters to be estimated. The variable $\overline{Z}_i$ refers to mean plot-specific characteristics (e.g. soil fertility, plot slope and drainage level), and θ_j denotes the corresponding parameters to be estimated. This is essential in order to account for unobserved heterogeneity due to plot varying characteristics being correlated with household level variables when a household cultivates multiple plots (Mundlak 1978). A Wald test of the null hypothesis that the

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vector θ_j are jointly equal to zero is conducted to indicate the relevance of plot-specific heterogeneity (Teklewold *et al.* 2013).

To ensure that the estimates of α_j in Equation 4 are unbiased and consistent, inclusion of selection correction terms derived from the multinomial selection process is required. We follow Bourguignon *et al.* (2007) and assume that the error terms (ε_{ij}) and u_{ij} are linearly correlated for every j option, such that the expected value of u_{ij} is stated as $E[u_1|\varepsilon_1,\ldots\varepsilon_j] = \sigma \sum_{j=1\ldots M} \rho_j\varepsilon_j$, where ρ_j is the correlation between u_{ij} and ε_{ij}, while σ is the standard deviation of the error term u_{ij}.

Thus, the outcome equation (Equation 4), taking into consideration the choices made with bias correction, can be restated as in Teklewold *et al.* (2013):

$$\begin{cases} \text{Regime } 1: y_{i1} = Z_{i1}\alpha_1 + \sigma_1\hat{\lambda}_{i1} + \overline{Z}_i\theta_j + \omega_{i1} \text{ if } V_i = 1 \\ \qquad \vdots \qquad\qquad \vdots \qquad\qquad \vdots \qquad\qquad \vdots \qquad\qquad \vdots \\ \text{Regime } M: y_{ij} = Z_{ij}\alpha_j + \sigma_j\hat{\lambda}_{ij} + \overline{Z}_i\theta_M + \omega_{ij} \text{ if } V_i = J \end{cases} \tag{5}$$

where $\lambda_{ij} = \sum_{k\neq j}^{M} \rho_j \left[\frac{\hat{P}_{ik}\ln(\hat{P}_{ik})}{1-\hat{P}_{ik}} + ln\hat{P}_{ij}\right]$ refers to the inverse Mills ratios computed from the estimated probabilities in MNL model in Equation 3, ρ_j is the correlation coefficient between the error terms ε_{ij} and u_{ij}, with the error terms ω_{ij} assumed to have a zero mean, and $\hat{P}_{ij}$ represents the estimated probability that plot i is treated with practice j.

2.3 Estimation of counterfactual and treatment effects

We estimate expected outcomes in the actual and counterfactual scenarios following Di Falco and Veronesi (2013) and Ng'ombe *et al.* (2017). Specifically, we first derive the expected outcomes of plots that were treated, which in our study means $j = 2,\ldots$M($j = 1$ is the reference category, i.e. non-adoption). From Equation 5, the conditional expectations for each outcome variable-based practice are chosen as follows:

Adopters with adoption (actual adoption observed in the sample):

$$\begin{aligned} E(y_{i2}|V_i = 2) &= \mathbf{Z}_{i2}\boldsymbol{\alpha}_2 + \sigma_2\hat{\lambda}_{i2} + \overline{Z}_i\theta_2 \\ E(y_{iJ}|V_i = J) &= \mathbf{Z}_{ij}\boldsymbol{\alpha}_j + \sigma_j\hat{\lambda}_{ij} + \overline{\mathbf{Z}}_i\boldsymbol{\theta}_j \end{aligned} \tag{6}$$

The counterfactual case that adopters did not adopt is also stated as:

$$\begin{aligned} E(y_{i1}|V_i = 2) &= \mathbf{Z}_{i2}\boldsymbol{\alpha}_1 + \sigma_1\hat{\lambda}_{ij} + \overline{\mathbf{Z}}_i\boldsymbol{\theta}_j \\ E(y_{i1}|V_i = j) &= \mathbf{Z}_{ij}\boldsymbol{\alpha}_1 + \sigma_1\hat{\lambda}_{ij} + \overline{\mathbf{Z}}_i\boldsymbol{\theta}_j \end{aligned} \tag{7}$$

The impact of adopting practice j is denoted as the average treatment effect on the treated (ATT), which is calculated by subtracting Equation 6 from 7 to obtain Equation 8 as follows:

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$$\begin{aligned} ATT &= E(y_{2i}|V_i = 2) - E(y_{i1}|V_i = 2) \\ &= Z_{i2}(\alpha_2 - \alpha_1) + \overline{\boldsymbol{Z}}_{i2}(\boldsymbol{\theta}_2 - \boldsymbol{\theta}_1) + \hat{\lambda}_{i2}(\sigma_2 - \sigma_1) \end{aligned}$$

The term $\hat{\lambda}_{ij}(.)$, together with the Mundlak device ($\overline{\boldsymbol{Z}}_{i2}$), accounts for selection bias and endogeneity due to unobserved heterogeneity.

The MESR approach enables consistent and efficient estimation of $\boldsymbol{\alpha}_j$ and accounts for a reasonable correction of bias in the outcome equations, even when the independence of irrelevant alternatives (IIA) assumption is not met (Bourguignon *et al.* 2007). Another advantage of using this approach is the ability to evaluate impact of both individual and combination of climate-smart practices (Di Falco and Veronesi 2013). Furthermore, it relaxes the restrictive assumptions of Lee's (1983)[2] selectivity model and provides a complete description of selectivity impacts on all options considered by farmers.

For proper identification of the MESR model, including some variables in vector $\boldsymbol{X}_i$ that are not included in vector, $\boldsymbol{Z}_i$ is recommended (Bourguignon *et al.* 2007). We use farmers' perception of drought, as well as access to climate information and association membership as identifying instruments. These variables intuitively influence farmers' decisions to adopt climate-smart agricultural practices but might not directly affect farm revenues (Di Falco and Veronesi 2013). We confirm the validity of these instruments by performing a falsification test, whereby a variable is considered as a valid instrument if it affects farmers' decisions to adopt a practice, but not the outcome variables among non-adopters (Di Falco and Veronesi 2013). We further performed a robustness check of our results by employing an alternative approach using multivariate treatment effects, which also accounts for unobservable factors in a multinomial choice and impact analysis framework (Deb and Trivedi 2006).

We control for potential endogeneity of some explanatory variables in our model, particularly off-farm work participation and extension visits. Off-farm work participation is potentially endogenous because adoption of some climate-smart practices is labour-intensive and households engaged in off-farm work may not be able to adopt such practices (labour-loss effect). On the other hand, income earned from off-farm work may be used to purchase inputs or invested in climate-smart practices (income-effect). In the case of extension visits, it is possible that farmers who are adopting may attract more visits by extension staff than non-adopters. Potential endogeneity of the variables was addressed using the control function approach (Wooldridge 2015). The approach involves the specification of the potential endogenous variable (i.e. off-farm work participation or extension visit) as a function of explanatory variables influencing adoption of each practice, together with a

[2] In Lee's method, a single selectivity term is estimated for all choices (Lee 1983; Bourguignon *et al.* 2007).

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set of instruments[3] in a first-stage probit regression (in the case of extension visit, we employed Poisson specification in the first-stage). Instead of using the predicted values of off-farm participation or extension visit variables, as in two-stage-least-squares, the observed values of the endogenous variables and the generalised residuals retrieved from a first-stage regression are included as covariates in the MESR model. Including the residuals serves as a control function, enabling the consistent estimation of the potentially endogenous variables in the MESR model (Wooldridge 2015).

3. Data and descriptive statistics

The data used in this study was obtained from a survey during the 2015/2016 cropping season in 25 communities across five districts and three regions in Ghana. A multistage sampling procedure was employed to select and interview 476 households (cultivating 1,001 plots) in Upper East (UE), Northern (NR) and Brong–Ahafo (BA) regions. Based on agroecology, we selected five districts from the three regions (Bongo and Talinse in UE, Tolon and Kumbungu in NR, and Techiman South in BA). Five communities were randomly selected from each district and 15-20 households from each community in proportion to the number of farmers in these communities. Finally, we obtained 203 households for NR cultivating 568 plots located in the Guinea Savannah, 147 households for UE in the Sudan Savannah, with 277 plots, and for BA in the Transitional zone, 126 households with 156 plots.

As indicated earlier, climate-smart practices include crop choice and soil and water conservation measures. Crop choice was practiced on about 18.58 per cent of plots. Soil and water conservation in this study refers to plots that were treated with minimum tillage soil, or stone bunds and organic manure. Soil and water conservation was practiced on 35.26 per cent of plots. In addition, 28.67 per cent of plots were treated with both crop choice and soil and water conservation measures, while 17.50 per cent of plots were considered as non-adopting plots. The descriptive statistics of all the variables are presented in Table 1. Since our sample is made up of farmers practicing mixed cropping, we constructed the crop revenue variable by summing up the value of all crops on a plot, following the example by Kato *et al*. (2011). The average reported crop revenue per plot is about 559 Ghana cedis (GHS). The crop revenue distributions by choice of practice are presented in Figure 1. The distributions show indications of negative skewness, with greater variance, for non-adoption, compared with cases of adopted practices.

Information was also taken on general household characteristics, access to climate change information, the type of crops cultivated (see Table A1) and various farming-related activities. Furthermore, farmers' perceptions on

[3] We used distance to district capital as an instrument in an auxiliary equation aimed at controlling for potential endogeneity of off-farm work participation. Also, distance to nearest agricultural extension office was used to instrument access to extension variable.

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drought occurrence and access to weather or climate information, and the practices being implemented to mitigate real or possible effects of drought and floods were captured. We also took information on farmers' reported plot characteristics, such as soil fertility, soil drainage level and slope of land.

We used rainfall and temperature data from the Global Weather Data of National Centers for Environmental Predictions (NCEP) climate data for the selected districts in Ghana, covering the period 1979-2014. Details of the climate data can be found at https://globalweather.tamu.edu/. The long-term

Table 1 Descriptive statistics of plot and household variables

Variables	Variable description	Mean	SD
Crop revenue	Total crop revenue per acre (GHS)†	558.86	749.37
Fertiliser	Expenditure on fertiliser (organic and inorganic) GHS	225.20	429.48
Herbicide	Expenditure on herbicide used GHS	77.40	438.43
Hired labour	Expenditure on hired labour GHS	147.63	13.13
Farm size	Cultivated farm size in acre	7.16	5.83
Education	Years of formal education	5.49	5.02
Household size	Number of people in a household	5.95	3.08
Age	Age of farmer in years	39.64	13.83
Gender	Male = 1, female = 0	0.86	0.35
Off-farm	Farmer is engaged in off-farm activity = 1, 0 otherwise	0.38	0.49
Livestock	Livestock ownership in tropical livestock units (TLU)‡	1.80	5.60
Extension	Number of extension visits	0.89	1.29
Distance-Capital	Distance to district capital	3.13	7.26
Distance-Ext	Distance to nearest extension office	1.39	4.22
Perception-drought	Perception of drought occurrence = 1, 0 otherwise	0.75	0.43
FBO-mem	Farmer belongs to a group/association = 1, 0 otherwise	0.30	0.46
Climate-info	Farmer receives current climate information = 1, 0 otherwise	0.57	0.49
Slope	Mean plot slope = 1 if farm has portions of steep slopes, 0 otherwise	0.58	0.43
Erosion	Mean erosion level = 1 if farmland has portions of moderate to severe erosion, 0 otherwise	0.90	0.53
Drainage	Mean plot drainage = 1 if farmland is well drained, 0 otherwise	0.46	0.42
Fertility	Mean fertility = 1 if soil is considered fertile, 0 otherwise	0.14	0.23
Non-adoption	Percentage of plots without no adoption	17.48	-
Crop choice	Percentage of plots with crop choice practice	18.58	-
Soil and water cons	Percentage of plots with soil & water conservation practice	35.26	-
Joint adoption	Percentage of plots with joint adoption of crop choice and soil and water conservation	28.67	-
Number of plots		1001	
Number of HH		476	

†Exchange rate at the time of the survey was USD 1 = GHS 4.26 (Source: WorldRemit).
‡TLU conversion factors are cattle = 0.7, sheep = 0.1, goats = 0.1, pigs = 0.2, chicken = 0.01.
SD refers to standard deviation.

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averages of temperature and rainfall and their coefficients of variations were calculated and used as explanatory variables in the selection and outcome equations. The coefficients of variation of the climate variables were used as proxies for climatic shocks. We employed spatial interpolation techniques to determine household-specific rainfall and temperature values, using the household location-specific coordinates (latitude, longitude and elevation) that were gathered through the survey (Wahba 1990; Di Falco and Veronesi 2013). The interpolated climate data was merged with survey data at the household level, using the location/household identification variable generated during the field survey.

Furthermore, we included a number of control variables in our empirical specification. These include household characteristics (such as age of the head, education level of the head of the household, household size and gender), farm inputs (fertiliser, herbicides) and ownership of resources (such as livestock ownership, farm size). These variables were included in line with the empirical literature on climate-smart agriculture, technology adoption and impact assessment (e. g. Di Falco and Veronesi 2013; Kassie *et al*. 2014). The means of various variables related to the alternative choices are reported in Table A2 in the Appendix 1. Although significant differences could be observed with respect to crop revenues among alternative practices, these differences do not account for selection bias arising from both observable and unobservable factors. These difference might also imply that these variables can influence farm performance differently, based on choice of climate-smart practice implemented. This further justifies our decision to employ the MESR in the analyses.

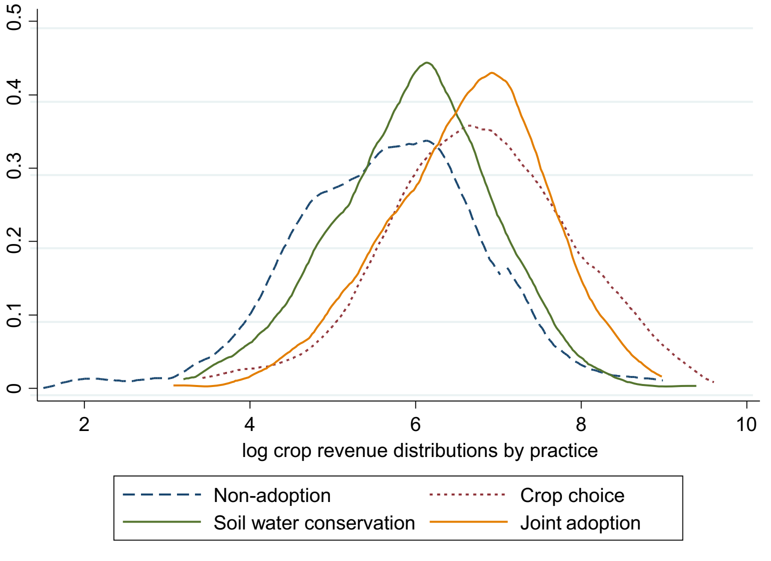

Figure 1 Kernel density distributions of crop revenue by adoption status. [Colour figure can be viewed at wileyonlinelibrary.com

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4. Results and discussions

4.1 Determinants of adoption of climate-smart practices

The results of the determinants of adoption of climate-smart practices are presented in Table 2. The reference practice is non-adoption. The MNL model fits the data well, with the Wald test, $\chi^2 = 666.23, p > \chi^2 = 0.000$, rejecting the null hypothesis that all the regression coefficients are jointly equal to zero. The instruments (perception-drought, FBO-memb and Climate-info) employed to identify the MESR are also jointly significant. A falsification test on the excluded instruments also showed that the instruments jointly influenced adoption at all levels, but not crop revenue or risk exposure of non-adopters (see Table A3 in the Appendix 1).

The results indicate that characteristics of the household head, household endowments, inputs, climate and plot-specific variables influence the adoption decisions of individual, crop choice only, soil and water conservation only, and joint adoption. Particularly, erosion and drainage levels (*Erosion, Drainage*) positively and significantly influence adoption of individual (crop choice only, soil and water conservation only) as well as joint adoption. Similar findings have been reported in Ethiopia by Di Falco and Veronesi (2013) and by Ng'ombe *et al.* (2017) in Zambia, underscoring the importance of capturing farm-level characteristics in designing and implementing effective farm-level climate-smart practices.

The results show that the coefficient of the age variable is negative and statistically significant in all practices signifying that an increase in age of the farmer leads to a decrease in the likelihood of adoption of climate-smart practices. The results also reveal a positive and significant effect of household size on adoption of crop choice only, as well as on soil and water conservation. The stronger effect of household size on adoption of soil and water conservation is consistent with expectations, considering the labour-demanding nature of this particular practice. The coefficient of the variable education is positive and significant for individual and combined strategies, a finding that is consistent with previous studies (e.g. Abdulai *et al.* 2011; Di Falco and Veronesi 2013).

The coefficient of the variable livestock ownership variable (TLU) is positive and significant for all practice choices, indicating that livestock ownership could enhance adoption. Among the inputs, herbicides and fertiliser positively and significantly influence the implementation of individual and joint adoption choices. The use of herbicide is becoming common among smallholders in Ghana due to the labour-saving nature of this input, especially during land preparation and weed control. However, farmers' engagement in off-farm activity appears to negatively and significantly influence adoption of all climate-smart practices, alluding to the fact that off-farm activity engagement and adoption of these practices may be competing for household labour resulting in the labour-loss effect (Taylor *et al.* 2003;

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Table 2 Parameter estimates of adoption of climate-smart practices: multinomial logit selection model†

Variables	Crop choice (n = 186)		Soil and Water cons (n = 353)		Joint Adoption (n = 287)	
	Estimate	SE	Estimate	SE	Estimate	SE
Constant	-76.84	135.36	-61.63	540.40	-559.63	577.73
Age	-0.72**	0.31	-0.73**	0.26	-1.13***	0.28
Gender	19.23**	6.63	41.45***	6.32	14.90**	5.69
Household size	0.43**	0.18	0.72***	0.16	0.18	0.15
Education	0.95**	0.39	2.47***	0.37	0.84**	0.33
Farm size	2.27**	0.98	5.69***	0.93	1.41*	0.85
Livestock	5.17**	1.96	12.61***	1.88	4.55**	1.67
Off-farm	-8.44***	2.71	-17.66***	2.60	-7.09***	2.33
Fertiliser	1.86**	0.71	4.53***	0.68	1.63**	0.61
Herbicide	0.82***	0.26	1.870***	0.25	0.96***	0.23
Rainfall	-0.06	0.05	0.03	0.05	0.02	0.05
Temp	21.62	13.51	8.04	12.33	1.54	12.34
RFanom	11.66**	4.38	6.88*	3.77	0.13	4.17
Tem-anom	1.01*	0.53	1.12**	0.31	0.65***	0.22
Tem x RFanom	0.27*	0.14	0.05	0.12	0.52***	0.13
Extension	0.26**	0.10	0.52**	0.21	0.40*	0.22
Slope	-7.56**	2.62	-18.53***	2.53	-7.65**	2.30
Erosion	18.81***	7.19	46.12***	6.86	15.12***	6.15
Drainage	10.18***	3.16	21.48***	3.04	8.39***	2.74
Fertility	1.13	0.80	4.50***	0.77	1.82**	0.74
Perception-drought	1.72***	0.31	1.80***	0.26	0.391***	0.12
FBO_memb	0.96***	0.30	1.22***	0.28	0.52*	0.28
Climate-info	0.37	0.28	0.44*	0.25	1.08***	0.26
Resid-Off-farm	-1.55	4.04	8.48	5.41	5.28	3.44
Resid-Extension	0.28	0.37	0.09	0.36	0.38	0.35
Joint sig instruments (χ^2) in crop revenue equation	42.80***		65.64***		23.25***	
Joint sig instruments (χ^2) in Skewness equation	64.41***		41.33***		23.17***	
Wald test, χ^2 (69)	666.23					
N	1001					

Note: Preliminary estimates with multivariate probit showed a positive significant correlation between crop choice and soil and water conservation with *a*Rho = 0.327and Likehood Ratio LR = 27.38.
***, **, * represent 1%, 5% and 10% significance level, respectively.
†Reference category is non-adoption.

Rakshandrah and Abdulai 2015). As noted earlier, the potential endogeneity of off-farm work participation was addressed using the control function (CF) approach and the estimate of the residual term (*Resid-Off-farm*) from the first stage of CF regression[4] is not significant in all choices, signifying the exogeneity of off-farm participation in the model (Wooldridge, 2015). The results also show that extension visits (*Extension*) positively and significantly influence adoption of all climate-smart practices, a finding that is in line with

[4] The first-stage estimates of the control function results are available but not reported here to save space.

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that of Teklewold *et al*. (2013), who argue that adoption of climate-smart practices as package is knowledge-intensive and therefore requires skilled extension staff to facilitate the adoption process.

Interestingly, from the results, rainfall anomalies (*RFanom*) positively and statistically influence the adoption of crop choice only and weakly with soil and water conservation. Also, mean temperature (*Temp*) positively influences joint adoption, while temperature anomalies (*Tem-anom*) positively and significantly influence adoption of all strategies. We included an interaction term between temperature and rainfall variability (*Tem* x *RFanom*). The results show that increasing variability in rainfall, combined with rising temperature would likely influence the adoption of crop choice only and joint adoption, but not necessarily soil and water conservation only, a finding that is consistent with the results reported by Moniruzzaman (2015). The positive effect of temperature and its anomalies on adoption (particularly joint adoption) probably implies that farmers could be employing soil and water conservation measures such as stone and soil bunds, together with crop choice to cope with rising temperature or its fluctuations. Thus, despite the labour-intensive nature of soil and water conservation practices (World Bank 2009), they can be more useful as climate adaptation measures in areas prone to erratic rainfall regimes or high temperatures.

Furthermore, the coefficient of the variable representing group membership (*FBO-memb*) is positive and significantly different from zero, suggesting that association membership increases the propensity to adopt crop choice as well as soil and water conservation strategies. This finding supports the notion that farmers' association membership plays a significant role as source of information on input and innovations (Mutenje *et al*. 2016). The coefficient of the variable representing farmers' perception about drought occurrence (*Perception-drought*) is also positive and significantly associated with adoption of individual and combined choices, suggesting that upgrading farmers' climate change awareness enhances the adoption of climate-smart practices.

4.2 Determinants of crop revenue and skewness: Second-stage MESR model

In Table 3, we present the determinants of crop revenues and skewness (downside risk exposure) by choice of climate-smart practices. The selectivity correction terms, denoted as m_1, *m2, m3* and *m4,* capture selectivity effects arising from unobserved factors. The estimated variances are all bootstrapped with 100 replications to deal with heteroscedasticity as suggested by Bourguignon *et al.* (2007). The results show that the selectivity correction terms are significant in the revenue equations for non-adoption, soil and water conservation only and joint adoption options, indicating the presence of sample selectivity effects and using OLS would have produced biased and inconsistent estimates. Thus, accounting for selectivity effects is essential in obtaining consistent estimates in the MESR model.

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Turning to the effects of other variables, the results in Table 3 further demonstrate that herbicide use significantly influences crop revenue among adopters of soil and water conservation only and joint adopters, but not crop choice only. This implies that application of herbicide could be a complementary input in effective adoption of soil and water conservation and result in high crop revenue. Rainfall anomaly (*RFanom*) has a negative and significant effect on crop revenue, with greater magnitude among non-adopters, suggesting that adoption of climate-smart practices might have played a role in minimising the negative effect of rainfall anomaly on crop revenue among adopters. This finding is consistent with Food and Agriculture Organization's principle of climate-smart agricultural practices that seek to enhance farmers' resilience and ability to adapt to climate variability (FAO 2013). The coefficient of plot-level fertility (*Fertility*) has the expected positive sign on crop revenue, particularly for adopters of soil and water conservation and joint adoption. Off-farm work participation (*Off-farm*) positively significantly influences crop revenue, implying possible income effect of off-farm work participation on farm output. The effect of other variables on the skewness or downside risk exposure by climate-smart practice is reported in Table A4 in the Appendix 1[5].

4.3 Impact of adoption of climate-smart practices on crop revenue and risk exposure

The impacts of adoption of individual and combined climate-smart practices on crop revenue and skewness (risk exposure) are presented in Table 4. Here, expected crop revenue (log) under the observed case that the farmer adopted the strategies, and the counterfactual situation that they did not adopt are indicated. The results show that the adoption of crop choice and soil and water conservation practices leads to significant improvement in crop revenues. The highest log revenue effect (1.149) is obtained from the joint adoption of crop choice and soil and water conservation strategies (approximately 20.6 per cent), which is greater than the effect of each practice adopted independently, suggesting complementarity of the two climate-smart practices. In particular, the impacts of adoption of crop choice only, and soil and water conservation only are 13 per cent and 12 per cent increase in crop revenues, respectively. These findings are consistent with the results reported by Teklewold *et al*. (2013) for Ethiopia and Ng'ombe *et al*. (2017) for Zambia. The results also show that in all the counterfactual cases, adopters would have had lower crop revenues if they had not adopted.

The results also reveal that the adoption of crop choice and soil and water conservation individually or jointly significantly increased crop revenue skewness, which indicates a reduction in the probability of crop failure or revenue loss. Specifically, adoption of individual options results in increased

[5] For brevity, these estimates are not discussed in here.

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Table 3 Determinants of log crop revenue by climate-smart practices: second-stage MESR estimation

Variables	Non-adoption (n = 175)		Crop choice (n = 186)		Soil and Water cons (n = 353)		Joint adoption (n = 287)	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Constant	3.26	3.45	-3.43	4.38	-0.242	1.13	-0.54	3.29
Age	0.19*	0.10	0.22	0.17	-0.067	0.07	0.102	0.07
Gender	-0.930*	0.50	-1.14	9.21	3.148	3.76	-4.51	4.17
Household size	-0.05	0.14	-0.20	0.24	0.07	0.06	-0.052	0.11
Education	0.63**	0.28	0.70	0.54	1.21**	0.24	0.33	0.23
Farm size	-2.15**	0.74	-2.39*	1.28	0.03	0.61	-1.86**	0.64
Livestock	3.30**	1.38	3.56	2.66	1.96**	0.23	1.54**	0.21
Off-farm	4.22**	1.97	4.35*	2.58	1.18**	0.59	3.30*	1.67
Fertiliser	1.17**	0.51	1.32	0.96	1.32*	0.43	0.69***	0.23
Herbicide	0.53**	0.22	0.506	0.34	1.19**	0.13	1.17**	0.14
Rainfall	-0.05	0.04	0.035	0.05	0.01	0.01	0.001	0.04
Temp	-9.30	10.75	1.14	1.36	0.68	3.62	-2.16	10.28
RFanom	-2.93**	1.11	-1.27**	0.49	-1.99	0.51	-1.16***	0.14
Tem-anom	-5.71*	2.98	-2.98*	1.57	-1.00	1.13	-0.58	0.48
Temp x RFanom	0.11	0.21	0.03	0.10	0.89	0.56	0.54	0.42
Extension	1.72**	0.74	1.85	1.43	5.71**	2.34	8.78**	4.33
Slope	-5.68***	1.80	4.14	3.34	-1.16	1.65	1.958	1.54
Erosion	-1.19**	0.45	-1.30	1.02	-4.16	4.25	-5.22**	2.69
Drainage	-5.058**	2.23	-5.38	4.36	1.47	1.89	-2.79	1.98
Fertility	1.55**	0.53	1.60	1.06	1.35**	0.48	0.71**	0.33
Selectivity terms								
m1	-0.16	0.51	-1.92	1.31	1.58*	0.89	1.43*	0.85
m2	1.68	2.08	0.34	0.51	-1.99**	0.75	0.48	0.50
m3	-1.82*	0.95	2.70	1.66	0.50	0.49	0.25	0.86
m4	-1.68	1.12	-1.27	1.07	-0.89	1.05	0.05	0.38

***, **, *Represent 1%, 5% and 10% significance level, respectively. Bootstrapped standard errors in parentheses.

skewness by 32 per cent and 35 per cent for crop choice and soil and water conservation, respectively. The joint adoption of the two practices results in a 40 per cent increase in skewness, indicating complementarity in lowering the probability of crop failure. These results confirm earlier findings by Kassie *et al*. (2014) for farms in Malawi that adoption of on-farm climate-smart practices decreases farmers' exposure to downside risk and therefore reduces the probability of crop failure.

To provide further information about the impacts of individual and combination of climate-smart practices, we disaggregated the adoption impacts (ATT) by agro-ecological zones. The results demonstrate that joint adoption of the two practices has the highest positive and statistically significant impact on crop revenues for plots in the Sudan Savannah (ATT = 0.955). However, joint adoption has no significant impact on crop revenues in the Transitional zone. Interestingly, joint adoption appears to reduce downside risk in all agro-ecological zones. This location-specific impact analysis provides important additional information that could be

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Table 4 Average treatment effects of adoption of individual and combined strategies on log crop revenue and downside risk

Outcome	Adoption decision		ATT	ATT by Agro-ecological zone			
	If adopters adopted	If adopters had not adopted		Change in outcome (%)	Sudan Savannah	Guinea Savannah	Transitional Zone
Log crop revenue							
Crop choice	5.848	5.192	0.656***(0.088)	12.63	0.262**(0.091)	0.252**(0.128)	0.519***(0.160)
Soil and Water conservation	5.978	5.356	0.622**(0.227)	11.62	0.884***(0.075)	0.222***(0.056)	0.235*(0.129)
Joint adoption	6.714	5.565	1.149***(0.100)	20.64	0.955***(0.084)	0.126**(0.058)	0.115(0.411)
Skewness (downside risk)							
Crop choice	1.280	0.970	0.310***(0.018)	32.0	0.202***(0.001)	0.365***(0.045)	0.388***(0.054)
Soil and water conservation	-0.150	-0.231	0.081***(0.005)	35.0	0.162***(0.010)	0.193***(0.010)	-0.067*(0.039)
Joint adoption	0.734	0.523	0.211***(0.007)	40.4	4.341***(0.387)	4.293***(1.101)	2.390***(0.203)

***, **, * represent 1%, 5% and 10% significance level, respectively. Figures in brackets refer to standard errors.

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useful in promoting adoption of climate-smart agriculture in Ghana. A multivariate treatment effect regression (Deb and Trivedi 2006) was estimated as a robustness check[6], and the results which are presented in Table A5 in the Appendix 1 show positive impact of individual and joint adoption of climate-smart practices. The results of the multivariate treatment effect regressions are generally consistent with that of the MESR, except in the case of impact of soil and water conservation on crop revenue.

One probable explanation why the multivariate treatment effect estimate of soil and water conservation only is different (not significant) from the estimate from the multinomial endogenous switching regression model is that the former estimates population average treatment effect (ATE) while the later model estimates average treatment effect on the treated (ATT). Thus, if we were to rely on multivariate treatment effect, soil and water conservation only, as a climate-smart agricultural practice, we would have found it to have a statistically insignificant effect on farm revenues. However, with the multinomial endogenous switching regression model, the effect was positive and significant, a finding that is consistent with study by Abdulai and Huffman (2014) about effect of the practice on yield and farm revenues, while using the endogenous switching regression model. As noted by Clougherty *et al*. (2015), while the multivariate treatment effect approach involves only a shift of the intercept or the endogenous treatment, the multinomial endogenous switching regression (MESR) method involves the shift of the intercept, as well as differences in relevant coefficients of other treatments.

Overall, the findings emphasise the importance of adoption of crop choice and soil and water conservation among farmers as a means of managing ex-ante production risk, especially under climate uncertainty. The results do not support the notion that farmers who adopt climate-smart practices to avoid crop failure end up obtaining lower yields (Adamson *et al*. 2017). The findings further demonstrate some complementarity between crop choice and soil and water conservation practices as shown by the greater effect of joint adoption on both crop revenue and skewness of crop output. This finding would not have been possible if we had examined these climate-smart practices individually without considering the joint adoption effect.

5. Conclusions and policy implications

In this paper, we used farm-level data from three agro-ecological regions in Ghana to examine the determinants and impacts of adoption of two climate-smart practices (crop choice and soil and water conservation) on crop

[6] Following an anonymous reviewer's comment, we decided to do this analysis to compare the estimates of the multivariate treatment effects approach to the MESR method adopted in this study. While in the MESR approach, impact is determined by predicting outcomes and testing the differences between adopters of various choices and non-adopters, the marginal effects of the individual choices (relative to non-adoption) represent impacts in the multivariate treatment effects model.

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revenues and production risk exposure, measured as crop revenue skewness. We employed a multinomial endogenous switching regression (MESR) model to account for selectivity bias due to observable and unobservable factors. The empirical results showed that the highest crop revenue effect is obtained from the joint adoption of crop choice and soil and water conservation practices, suggesting complementarity in benefits. In addition, joint adoption of the two strategies significantly increased crop revenue skewness, implying that adoption lowers the probability of crop failure and therefore decreases the exposure to expected downside risk. A disaggregation of the adoption impacts based on agro-ecological zones revealed that plots in the dry savannah zones experienced higher impacts of joint adoption, compared to plots in the transitional zone. The findings also revealed that extension access, farmer education, climate anomalies and farmers' perception about drought and access to weather information are key determinants of adoption of crop choice and soil and water conservation measures.

Thus, policy interventions to increase agricultural productivity and reduce farmers' risk exposure should consider alleviating farmers' difficulties to adoption. For instance, government ministries (e.g. Ministry of Food and Agriculture) in collaboration with private agri-input dealers associations could facilitate the distribution of inputs, such as drought-tolerant seeds and herbicides, through certified agro-input outlets in farming communities, to enhance adoption. In addition, making quality climate information accessible to farmers will ease their adoption challenges including the right combination of practices to adopt. In view of the fact that effective adoption of climate-smart practices requires some knowledge and skills, enhancing farmer education and access to extension services should be among the policy measures that will facilitate adoption. This study particularly demonstrated that package adoption of crop choice, and soil and water conservation practices will enable farmers to benefit from the positive synergistic effects of joint adoption on farm performance and reduction in risk exposure.

The findings of this study should be considered with some caveats since we relied mainly on cross-sectional survey data. First, analysis of panel data would have enabled us to capture the dynamic effects of climate-smart practices on crop revenues and risk exposure. For instance, some climate-smart agronomic measures such as soil and water conservation measures (e.g. stone bunds and minimum tillage) take time to produce effects, and the effects of climate-smart practices may last over several cropping seasons. Second, an experiment to determine farmers' risk preferences would have been a more appropriate proxy for measuring and estimating risk exposure, but data on these measures are not available. Despite these caveats, we do not expect systematic bias in our assessment. Thus, this study contributes to the growing body of literature on climate-smart agriculture and how the adoption of specific farm practices affects farm performance in an area where there is limited access to formal risk reduction measures, such as agricultural insurance.

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Appendix

Table A1 The distribution of crops on plot of respondent farmers

Crop	% of plots
Maize	28.57
Rice†	14.38
Millet	11.24
Sorghum	7.37
Groundnut	14.19
Yam	2.94
Cassava	4.33
Vegetables	15.85
Number of plots	1,001

†Apart from rice, the rest of the crops were mostly intercropped.

Table A2 Means of variables by choice of climate-smart practices and pooled sample

Variables	Non-adoption	Crops choice only	Soil and water conservation only	Joint adoption	Pooled sample	SD
Crop revenue	473.77	606.74*	625.42**	665.02***	562.79	24.52
Off-farm	0.31	0.54	0.38	0.29	0.36	0.02
Age	38.10	40.40	40.04	36.27	38.91	0.42
Gender	0.75	0.83**	0.88***	0.93***	0.86	0.01
HH_size	6.17	5.96	6.59	7.72***	6.58	0.11
Education	4.18	5.99***	3.93	4.07	4.47	0.17
Farm size	5.99	7.18**	6.35***	8.63**	7.16	0.18
Fertiliser	254.28	236.91	249.97	337.17**	259.66	18.76
Hiredlabour	173.90	97.23*	125.46	190.72	147.63	13.13
Herbicide	131.71	38.13**	40.10**	130.30	77.40	13.86
Livestock	1.04	2.06**	1.77*	1.10**	1.80	5.60
Extension	0.51	1.01**	0.93***	1.19***	0.89	0.04
Perception-drought	0.59	0.86***	0.66**	0.87***	0.75	0.01
Climate-info	0.44	0.35*	0.22***	0.21***	0.29	0.25
FBO-mem	0.12	0.46***	0.45*	0.43**	0.30	0.46
Slope	0.58	0.43	0.70*	0.53	0.58	0.43
Erosion	0.82	0.53*	0.46	0.42	0.54	0.42
Drainage	0.56	0.32	0.90**	0.53	0.46	0.42
Fertility	0.24	0.33	0.46	0.42	0.14	0.23
N	175	186	353	287	1001	

*, **, *** denotes significance level at 10%, 5% and 1%, respectively.

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Table A3 Test of validity of instruments used to identify the MESR model

Variables	Crop revenue of non-adopters	Revenue skewness of non-adopters
Perception-drought	-0.149 (0.237)	0.273 (0.901)
Climate-info	-0.112 (0.170)	-1.020 (0.646)
FBO-memb	0.004 (0.172)	0.577 (0.654)
Constant	6.259*** (0.642)	1.198 (2.438)
F-tests on instruments	1.202 [p = 0.234]	1.160 [p = 0.327]

Note: Standard errors in parentheses. The values in the square bracket indicate the p-values of the F-test indicating the validity of the instruments used to identify the MESR model.

Table A4 Determinants of downside risk by climate-smart practices: second-stage MESR estimation (dep. variable: revenue skewness)

Variables	Non-adoption (n = 175)		Crop choice (n = 186)		Soil and water cons (n = 353)		Joint adoption (n = 287)	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Constant	0.89	2.08	-2.41	1.52	0.98	1.11	0.62	0.82
Gender	-0.41*	0.23	-0.72**	0.33	0.22	0.17	-0.20	0.14
HH_size	-0.44	0.58	-1.27*	0.71	0.42	0.36	-0.14	0.25
Education	2.82*	1.51	4.41**	1.97	-1.38	1.02	1.51	0.93
Farm size	-6.73*	2.78	-1.29**	0.52	2.32	2.63	-5.53**	2.70
Livestock	1.47	0.82	2.21**	0.99	6.49***	2.14	0.84*	0.48
Off-farm	-2.06*	1.12	-2.77**	1.37	0.90**	0.31	0.92**	0.45
Fertiliser	4.96*	2.70	8.11**	3.68	-2.43	1.90	2.80	1.71
Herbicide	-2.30	1.12	-3.09**	1.37	1.07	0.71	-1.09	0.73
Rainfall	-0.14	0.26	0.23	0.16	-0.10	0.13	-0.11	0.11
Temp	-0.25	0.64	0.77	0.48	-0.31	0.34	-0.18	0.25
RFanom	-0.07	0.11	-0.56**	0.21	0.16	0.15	0.60	0.97
Tem-anom	-0.39	0.33	-0.50	0.49	0.24	0.45	0.98	0.76
Extension	0.72	0.39	1.12**	0.53	-0.35	0.28	0.41	0.25
Slope	0.24	0.15	0.27**	0.12	-0.08	0.71	0.10	0.72
Erosion-level	-0.46	0.25	-0.84**	0.37	0.26	0.19	-0.25	0.16
Drainage	-0.23	0.12	-0.35**	0.16	0.11	0.86	-0.12	0.74
Fertility	0.66	0.44	0.84**	0.38	-0.15	0.21	0.35	0.20
Selectivity terms								
m1	-0.31	0.22	-1.08**	0.49	-0.82	0.67	-1.05	0.83
m2	0.29	1.02	0.20	0.22	0.01	0.61	0.65	0.58
m3	-0.63	0.65	-1.62***	0.22	0.01	0.40	-0.97	0.819
m4	-1.47**	0.58	-0.34	0.45	0.68	0.50	0.19	0.34

***, **, * represent 1%, 5% and 10% significance level, respectively. Bootstrapped standard errors in parentheses

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Table A5 Treatment effects of adoption on log crop revenues and downside risk: Multivariate treatment effect regression (Robustness check)†

Practice	Estimate	Standard errors
Log crop revenues		
Crop choice only	0.433**	0.222
Soil and water conservation only	0.151	0.171
Joint adoption	0.520**	0.204
Skewness (downside risk)		
Crop choice only	0.917***	0.254
Soil and water conservation only	0.327**	0.121
Joint adoption	0.963**	0.367

, * significant at 5% and 1%, respectively. Reference category is non-adoption.
†The entire results of the multivariate treatment effects regression are available on request.

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