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Impact assessment of Striga resistant maize varieties and fertilizer use in Ghana: A panel analysis

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Abstract

This study analyzes the impact of a component of climate-smart agriculture (CSA) technology—Striga-resistant maize (SRM) varieties and mineral fertilizer—on maize yield and food security using two rounds of panel data in Ghana. The study employs a multinomial endogenous switching regression model and finds that joint adoption of SRM varieties and mineral fertilizer increased maize yield by 872 kg/ha, food consumption scores by 17, and consumption per adult equivalent unit by 38 kg/ha. The positive impact of maize yield is high among adopters of multiple CSA technologies. The result is robust to an alternative endogeneity-correcting model and the implications of the findings are discussed.

KEYWORDS

climate-smart agriculture, Ghana, multinomial endogenous switching regression, welfare impacts

1 | INTRODUCTION

In sub-Saharan Africa, about 59% of the workforce live in rural areas and are engaged primarily in agriculture. The sector contributes significantly to the export earnings of the continent and is responsible for about a third of the GDP (Bjornlund et al., 2020; Lam et al., 2019). The importance of the agricultural sector to the economies of African countries does not mean that agriculture is the most productive sector of the economy (Bjornlund et al., 2020; Lam et al., 2019). Apart from socioeconomic constraints such as poor access to credit, low mechanization, and poor access to extension services, agricultural productivity across the continent is inhibited by biotic and abiotic factors such as poor or declining soil fertility, drought, Striga weed infestation, use of low-yielding varieties, and pests and diseases (Lobulu et al., 2019). Climate change and variability coupled with very low levels of irrigation further constrain agricultural productivity (Ochieng et al., 2016).

In Ghana, maize is the most important cereal crop produced and consumed. It accounts for about 53% of total cereal production in 2020 and is the most widely cultivated crop (Ministry of Food and Agriculture, MoFA, 2021). A wide range of food and non-food products are obtained from the grain, leaf, tassel, cob, and stalk. Despite the importance of maize in Ghana, the productivity of the crop is low when compared to potential yields and yields in other middle-income countries. Whereas the mean yield in Brazil is 6.1 Mt/Ha (Adjei & Kyerematen, 2018), that of Ghana is only 2.48 Mt/Ha (MoFA, 2021). In 2020, about 226,909 hectares of farmlands (16,909 ha for existing schemes, 189,000 ha for informal irrigation for smallholder farmers, and 21,000 ha for large-scale commercial farmers) in Ghana were under irrigation (MoFA, 2021) with crop producers applying, on average, just 223.18 kg of mineral fertilizer on every hectare of land (Adzawla et al., 2022). In addition, *Striga hermonthica* is an invasive weed that threatens the livelihoods of many farm households leading to almost 100% crop losses (Yacoubou et al., 2021). Most farms invaded by Striga are abandoned due to the high costs of weedicide and labour.

To address the problem of low productivity, climate-smart agriculture (CSA[1]) mineral fertilizer with different blends, and Striga-resistant maize (SRM) varieties has been promoted. The Maize Program of the International Institute of Tropical Agriculture has been working with the Maize Program of Ghana's Council for Scientific and Industrial Research to continuously develop maize varieties that combine earliness (in terms of maturity) with tolerance to Striga infestation (Badu-Apraku et al., 2010). Given the direct relationship between soil productivity and yield and the important role mineral fertilizer plays to enhance the performance of improved maize varieties, the Government of Ghana has been promoting the use of mineral fertilizers for soil amendments. The joint adoption of fertilizer and SRM is expected to increase yield, income, and food security.

There is some information on how the adoption of drought-tolerant maize varieties (DTMV) and fertilizer impacts household welfare. Martey et al. (2020) relied on cross-sectional observation and instrumental variable regression to estimate the factors that influence farmers' decision to cultivate DTMV and how that choice impacts yield, the intensity of commercialization, and farm income in northern Ghana. Martey and Kuwornu (2021) modelled how individual and joint adoption of row planting and DTMV affect farm and household outcomes through the application of a multinomial endogenous switching regression model to panel data from Ghana. In Nigeria, Abdoulaye et al. (2018) relied on cross-sectional data to assess the impacts of improved maize variety (encompassing hybrid, open-pollinated, and drought-tolerant maize varieties) adoption on yield and household welfare using the endogenous switching regression approach. A couple of papers rely on cross-sectional data from Zambia and apply propensity score matching methods, inverse probability weighted regression adjustment methods, or endogenous switching regression models to estimate the impact of the adoption of DTMV on yield, yield variability, downside risk, crop income, consumption expenditure, and food security (Khonje et al., 2015; Manda et al., 2018; Wossen et al., 2017). There are also studies in Ethiopia that estimate factors that influence the adoption of improved maize varieties and the consequences of adoption on household welfare based on econometric analyses of both panels (Bezu et al., 2014; Kassie et al., 2018) and cross-sectional data (Ahmed et al., 2017; Zeng et al., 2017).

The previous studies highlighted factors such as access to agro-inputs, agricultural extension, factors of production, and location in determining the decision to use DTMV and the consequent positive effect on farm and household welfare. However, Striga infestation is another major problem that causes substantial yield losses.[2] Unlike studies on the impacts of DTMV, the authors are not aware of any study that examines how the adoption of Striga-resistant maize varieties (with or without the use of inorganic fertilizers) affects household welfare. In addition to an empirical contribution on the welfare effects of adopting Striga-resistance maize varieties, this study relies on a time-invariant estimation technique that corrects for endogeneity to generate robust evidence to guide development practitioners on the factors to consider when implementing maize interventions that seek to improve yield and food security. We specifically use a multinomial endogenous switching regression model to analyze how an individual or joint adoption of Striga-resistant maize varieties and mineral fertilizer impact maize yield and food security in Ghana using two rounds of panel data.

The rest of the paper proceeds as follows. Section 2 contains our empirical strategy where we motivate the multinomial endogenous switching regression model. We describe our data generation process and present the descriptive statistics of the data in Section 3. We present and discuss our findings in Section 4. Section 5 contains the conclusions and implications of our study.

2 | EMPIRICAL STRATEGY

We estimate the effect of climate-smart agricultural technology adoption (Striga-resistant maize variety and mineral fertilizer) on farm and welfare outcomes using the following specification:

$$Y_{ijt} = \eta + \beta \mathrm{CSA}_{jti} + \gamma X_{ijt} + \tau_g + c_i + \mu_{ijt} \tag{1}$$

where Y is a measure of the farm and welfare outcome (yield, household dietary diversity score (HDDS), food consumption score (FCS), and consumption per AEU) of a farmer i living in household j at time t; CSA represents an indicator variable for CSA adoption (Striga-resistant maize variety and mineral fertilizer); α, β, and γ are vectors of parameters to be estimated; τ indicates region fixed effects which accounts for regional variations in terms of poverty, infrastructure, institutional support, and agroecology; c is unobserved time-constant factors; and μ is a mean zero, identically and independently distributed (iid) random error assumed to be uncorrelated with the explanatory variables. We also control for a vector of farmer and household characteristics, X which is reported in Table 1. The coefficient on CSA is

TABLE 1 Descriptive statistics of outcome and explanatory variables by survey year

	2013		2018		Pooled	
Variable	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Outcome variables						
Yield (kg/ha)	1074.15	741.40	1001.19	759.68	1033.20	752.16
Household dietary diversity score (number)	6.29	1.06	6.26	1.04	6.27	1.05
Food consumption scores (number)	60.43	20.29	59.46	20.02	59.89	20.13
Consumption per AEU (kg/AEU)	57.58	66.38	68.33	84.20	63.61	77.03
Policy variables						
Planted Striga-resistant variety (1 = yes)	0.11	0.31	0.07	0.25	0.08	0.28
Use mineral fertilizer (1 = yes)	0.49	0.50	0.44	0.50	0.46	0.50
Demography						
Sex of household head (1 = male)	0.78	0.42	0.77	0.42	0.78	0.42
Age of household head (years)	44.10	11.74	49.49	11.00	47.13	11.63
Years of education (years)	6.38	5.07	5.74	5.64	6.02	5.41
Marital status of head (1 = married)	0.91	0.29	0.87	0.34	0.88	0.32
Nativity status (1 = native)	0.63	0.48	0.64	0.48	0.64	0.48
Farm characteristics						
Model farmer (1 = yes)	0.25	0.43	0.11	0.31	0.17	0.38
Farmland inherited (1 = yes)	0.25	0.43	0.31	0.46	0.28	0.45
Slope of farmland (1 = slope)	0.55	0.50	0.69	0.46	0.63	0.48
Practice row planting (1 = yes)	0.77	0.42	0.99	0.09	0.89	0.31
Experience erosion on farmland (1 = yes)	0.17	0.38	0.20	0.40	0.19	0.39
Access to improved seed (1 = yes)	0.22	0.41	0.21	0.41	0.22	0.41
Distance to farmland (km)	35.39	19.73	38.08	19.74	36.72	19.77
Assets						
Own bicycle (1 = yes)	0.96	0.21	0.45	0.50	0.67	0.47
Own a sprayer (1 = yes)	0.97	0.17	0.53	0.50	0.72	0.45
Risk behaviour						
Risk (1 = highly impatient)	1.00	0.00	0.94	0.23	0.97	0.17
Averse to risk (1 = yes)	0.70	0.46	0.68	0.47	0.69	0.46
Institutional						
Access to STM seed and extension (1 = yes)	1.00	0.05	0.60	0.49	0.78	0.42

Abbreviation: SD, standard deviations.

Source: Author's computation based on IITA-IFPRI panel survey, 2018.

expected to be significant and either positive ($\beta > 0$) or negative ($\beta < 0$) depending on the outcome. Based on the condition of the randomness of treatment, β accurately measures the impact of CSA adoption on the outcomes. However, the assignment of the treatment is non-random.

Estimation of Equation (1) using the Ordinary Least Squares (OLS) method will lead to a biased and inconsistent estimate given that the adoption decision is endogenous. First, farmers may self-select into adoption decisions which may be influenced by unobserved human characteristics (such as motivation, preferences, and level of innovativeness) and soil characteristics (soil quality and fertility). Following Martey et al. (2020), risk-loving farmers are likely to adopt combinations of CSA practices while risk-averse farmers may be more likely to adopt a single CSA practice. Second, there is a potential reverse causality between CSA and the outcome variables. For example, the adoption of CSA is likely to influence yield and the farmers who record high yield or income are more likely to adopt CSA. In view of the above challenges, there is a need to address the endogeneity issues. Finally, the endogeneity could also emanate from unobserved heterogeneities among household heads and household characteristics.

We addressed the endogeneity issue by implementing the multinomial endogenous switching regression (MESR)[3] to account for selection bias and endogeneity arising from observed and unobserved heterogeneity. The MESR corrects for the selection bias by computing an inverse Mills ratio (IMR) based on the theory of truncated normal distribution (Bourguignon et al., 2007; Malikov & Kumbhakar, 2014). Second, the MESR allows for the construction of a counterfactual based on returns to the characteristics of CSA technologies adopters and non-adopters (Kassie et al., 2018). Third, the MESR allows for interaction between CSA technology choice set and the explanatory variables to account for the effect of CSA on the shift of the intercept and slope of the outcome equation (Abdoulaye et al., 2018; Di Falco & Veronesi, 2013). Finally, the model provides the differential effect of CSA technologies on the outcomes (Wu & Babcock, 1998).

The MESR involves a two-stage simultaneous estimation technique where the first stage model farmers' choice of CSA using a multinomial logit selection (MNLS) model and accounts for unobserved heterogeneity. The second stage is the outcome equation estimated with the OLS where the IMR computed from the first stage is included as an additional variable to account for selection bias from time-varying unobserved heterogeneity. A detailed description of the theoretical foundation of the first stage, second stage, and computation of the average treatment effects on the treated is published elsewhere (Khonje et al., 2018; Martey et al., 2020).

Based on the assumption that the household-specific heterogeneity and time-varying unobserved factors or idiosyncratic error are independent and identically Gumbel distributed across all CSA choice sets (Bourguignon et al., 2007), the probability (P_{jit}) that a farmer i at time t will choose technology j can be expressed as:

$$P_{jit} = \Pr\left(\rho_{1it} < 0 \mid X_{jit}\right) = \frac{\exp\left(\delta_j X_{jit} + \varphi_j \overline{X}_{ji}\right)}{\sum_{k\neq 1}^{j} \exp\left(\delta_k X_{kit} + \varphi_k \overline{X}_{ki}\right)} \quad (2)$$

where Equation (2) is the multinomial logit model (McFadden, 1973). The selectivity bias[4] is corrected based on the Bourguignon et al. (2007) approach where the underlying selection process follows a polychotomous normal model, allowing correlations between alternatives. We estimate Equation (2) using a pooled MNLS model which corrects for unobserved heterogeneity using the Mundlak (1978) and Wooldridge (2010) approach where the time-invariant unobserved effect (c_i) is modeled as a linear projection of the means of all time-varying observed explanatory variables ($\overline{X}_{ji}$) as: $c_i = \pi \overline{X}_{ji} + \alpha_i$. The IMR derived from the MNLS model is used as selection correction term in the second stage of the MESR model.

Following the approach by Khonje et al. (2018), the outcome equation for each possible regime j with selection bias correction term is specified as:

$$\begin{cases} \text{Regime1}: Y_{1it} = \beta_1 M_{1it} + \sigma_1 \hat{\lambda}_{1it} + \vartheta_1 \overline{M}_{1i} + \mu_{1it} \text{if} U = 1 \\ \quad \vdots \qquad\qquad\qquad\qquad\qquad\qquad j = 2, 3, 4 \\ \text{Regime}J: Y_{jit} = \beta_j M_{jit} + \sigma_j \hat{\lambda}_{jit} + \vartheta_j \overline{M}_{ji} + \mu_{jit} \text{if} U = J \end{cases} \quad (3)$$

where Y_{jit} represent outcomes associated with the selected regime $j (j = 0, \ldots, J)$ and observed if only one of the possible combinations of CSA practices is used, M_{jit} represents the vector of explanatory variables, $\overline{M}_{ji}$ represents the means of all time-varying variables included to control for unobserved heterogeneity (Mundlak, 1978; Wooldridge, 2010), σ is the covariance between ε_{jit} (first stage) and μ_{jit} (second stage), and $\hat{\lambda}_{jit}$[5] is the IMR calculated from estimated probabilities in Equation (2). Following the advice of Di Falco (2014) and other studies (Kassie et al., 2015; Khonje et al., 2018; Zeng et al., 2017), we included an exclusion restriction for the identification.

Following previous studies and drawing lessons from the social learning literature (Conley & Udry, 2010; Krishnan & Patnam, 2014; Magnan et al., 2015; Pham et al., 2021; Verkaart et al., 2017), we computed the number of neighbours who practice CSA and has extension access which is computed as the proportion of community j adopters of CSA or farmers with access to extension minus the farmer under consideration, i. In terms of relevance of the instrument, farmers are more likely to adopt CSA technologies if their neighbours within the primary sampling unit (community) practice CSA and have access to extension services. Communities with active CSA adopters are more likely to attract the services of extension. This allows for information sharing at the local level which may influence farmers' decisions to adopt CSA technologies. The local level accounts for differences in resource endowment that may facilitate access to seed, fertilizer, and extension support services. We argue that the instrument will only affect the outcome variables only through the adoption of CSA practices and access to the extension. The admissibility of the instrument is established through a simple falsification[6] test proposed by Di Falco et al. (2011). The results confirm that the excluded variable have a significant effect on CSA technologies but do not significantly influence the outcome variables (Tables S1 and S2 in Appendix S1).

Finally, the actual expected outcomes of adopters are expressed as:

$$E\left(Y_{jit} \mid U = j, M_{jit}, \overline{M}_{ji}, \hat{\lambda}_{jit}\right) = \beta_j M_{jit} + \vartheta_j \overline{M}_{ji} + \sigma_j \hat{\lambda}_{jit} \quad (4a)$$

The expected outcomes of adopters had they decided not to adopt (counterfactual) is specified as:

$$E\left(Y_{1it} \mid U=j, M_{jit}, \overline{M}_{ji}, \hat{\lambda}_{jit}\right)=\beta_1 M_{jit}+\vartheta_1 \overline{M}_{ji}+\sigma_1 \hat{\lambda}_{jit} \quad (4b)$$

Equation (4b) represents the outcome of what CSA technology adopters would have obtained if the coefficients on their characteristics ($M_{jit}, \overline{M}_{ji}, \hat{\lambda}_{jit}$) had been the same as the coefficient on the characteristics of the non-adopters (Kassie et al., 2018; Khonje et al., 2018; Teklewold et al., 2013).

The ATT[7] is computed as follows:

$$\begin{aligned}\mathrm{ATT}&=E\left(Y_{jit}\middle|U=j, M_{jit}, \overline{M}_{ji}, \hat{\lambda}_{jit}\right)-E\left(Y_{1it}\middle|U=j, M_{jit}, \overline{M}_{ji}, \hat{\lambda}_{jit}\right)\\&=M_{jit}(\beta_j-\beta 1)+\hat{\lambda}_{jit}(\sigma_j-\sigma_1)+\overline{M}_{ji}(\vartheta_j-\vartheta_1)\end{aligned} \quad (5)$$

The first term of Equation (5) $\left(\beta_j-\beta_1\right)$ captures the expected change in the mean outcome due to the differences in coefficients of the observed characteristics. The second $\left(\sigma_j-\sigma_1\right)$ and third $\left(\vartheta_j-\vartheta_1\right)$ terms in Equation (5) corrects selection bias and endogeneity originating from unobserved heterogeneity (Khonje et al., 2018).

To complement the MESR technique, we implement the Lewbel two-stage least square (2SLS) estimation technique (Lewbel, 2012) to bind our estimates. This approach is useful when valid external instruments are unavailable or considered potentially weak. The Lewbel[8] 2SLS method allows the estimation of models with endogenous regressors using heteroscedasticity-based instrumental variables. This method exploits heteroskedasticity in the data to generate internal instruments that are used to address endogeneity.

3 | DATA AND DESCRIPTIVE STATISTICS

3.1 | Data

The empirical analysis uses farm household-level data. The study was conducted primarily in all the major maize-growing areas in Ghana except the Greater Accra Region of Ghana (Figure 1). The data were collected in the years 2013 (baseline) and 2018 (endline). The survey is representative at the national level and characterized by a low attrition rate. A multi-stage sampling technique (clustered and randomized sampling procedure) was employed in the selection of the farmers. The sampling procedure began with a proportional sampling that was used to assign weights to the maize-producing districts and was followed by a random sampling of the 30 districts. The second stage employed a random sampling technique to select 90 enumeration areas[9] (EAs) from the sampled 30 districts. Finally, seven farmers were sampled from each of the EAs bringing the total number of farmers to 630. To generate a panel unit, the survey was repeated in 2019 for 555 farmers. The sample size was reduced to 438 which represents an attrition rate of 20%. The attrition rate in our data was mainly due to migration, death, and non-availability.

In particular, the survey captured information on household demographic characteristics, farm-level characteristics, sustainable agricultural practices, soil improvement technologies, use of SRM varieties, institutional and social capital, risk preferences, and distribution of maize production. Adoption of SRM varieties refers to farmers who have cultivated the SRM variety for at least 1 year during the period of the survey. Similarly, fertilizer (FERT) adopters refer to farmers in the sample who have applied fertilizer to their maize plot for at least 1 year during the survey period. Based on the definitions, we constructed CSA adoption. An individual farmer is categorized as an adopter of CSA if the farmer has adopted both SRM variety and applied fertilizer to the maize plot for at least a year.

3.2 | Descriptive statistics

Table 1 describes the outcome and explanatory variables. The data show that the average yield, HDDS, FCS, and consumption per AEU are 1.03 tons/ha, 6.27, 59.89, and 63.61 kg, respectively. Compared to 2018, the yield and food security effects are higher in 2013 while consumption per AEU is higher in 2018 relative to 2013. The adoption of Striga-tolerant varieties decreased from 11% to 8% and mineral fertilizer use also decreased from 49% in 2013 to 44% in 2018. About 78% of the sampled farmers are males with 47 years of age and 5.4 years of formal education. Comparatively, marital status and nativity of household heads are almost the same across the sample periods. The percentage of farmers who are model farmers declined while the percentage of farmers who inherited their cultivated plots increased from 2013 to 2018.

With reference to the farm characteristics, the data show that farmers who cultivate on sloped farmlands, practice row planting, experience erosion, and have access to seed are 63%, 89%, 22%, and 19%, respectively. Farmers travel a distance of 37 km to access their farm plots. However, the distance travelled to the farm plots increased from 35 km in 2013 to 38 km in 2018. In terms of assets, 47% and 45% of the farmers have owned a bicycle and a sprayer, respectively. Regarding time and risk preferences, we find that 97% of the farmers are highly impatient while 69% are risk averse. About 78% of the farmers have access to SRM seed and extension services.

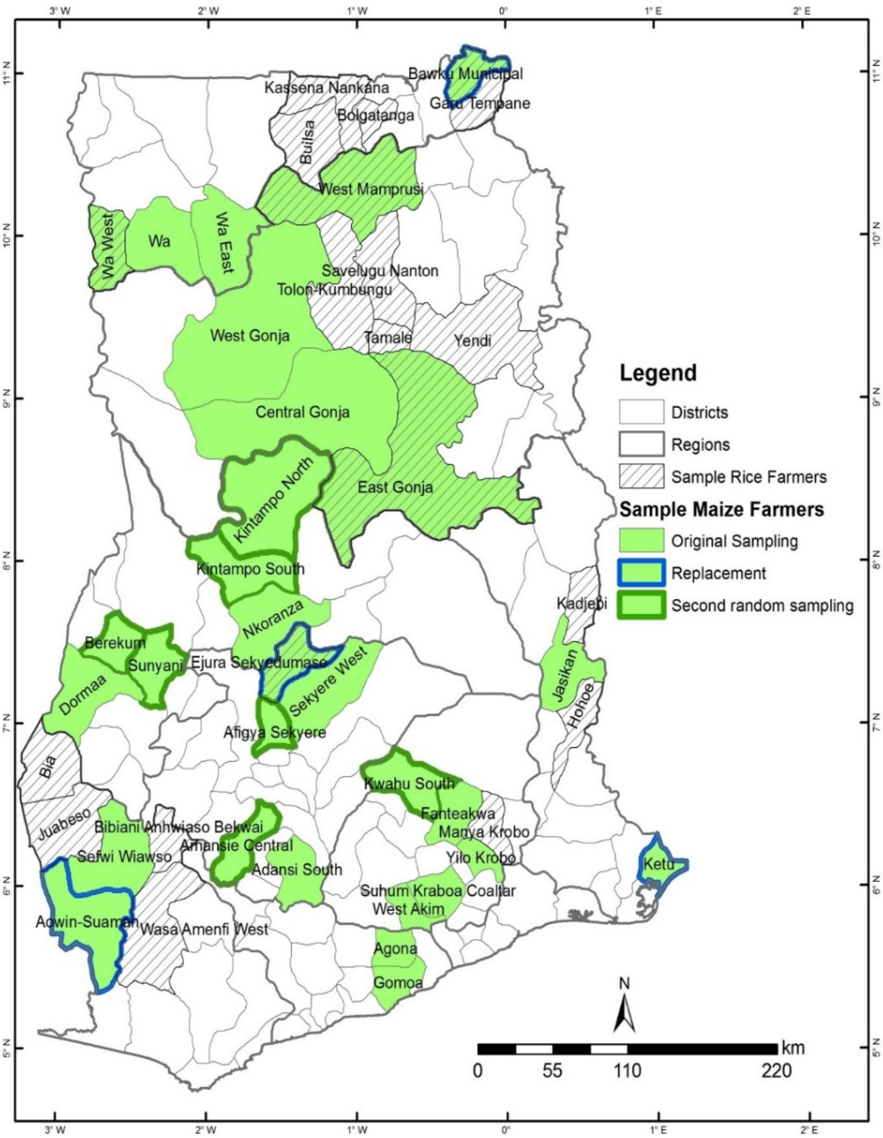


FIGURE 1 Sample districts for the maize and rice adoption study. *Source*: Ragasa et al. (2014)

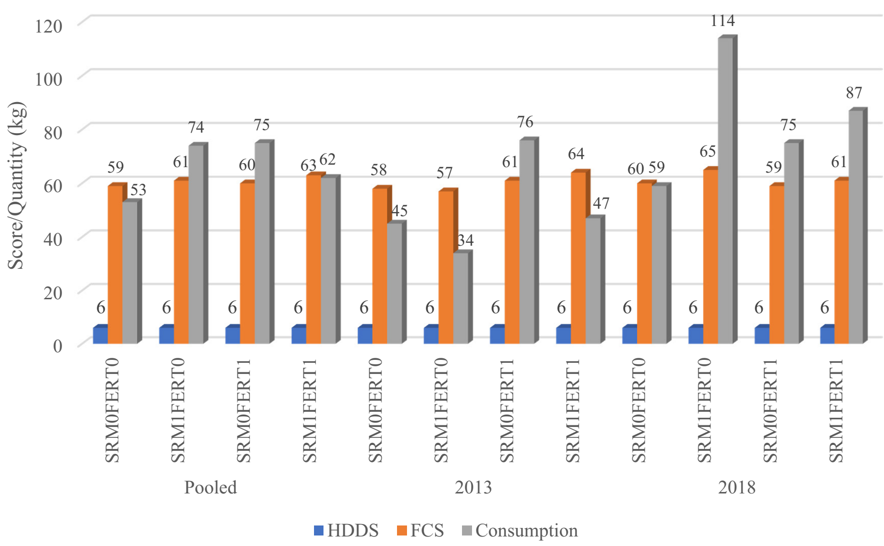


FIGURE 2 Food security outcomes per adoption category and year of survey. SRM1FERT0 is adopter of only Striga-resistant maize (SRM) varieties, SRM0FERT1 refers to adopters of only mineral fertilizers; SRM1FERT1 refers to adopters of both Striga-resistant maize varieties and mineral fertilizers; and SRM0FERT0 refers to non-adopters.

Figure 2 shows the food security outcomes per the adoption category of CSA technologies and the year of the survey. The average HDDS is similar across the different categories of CSA technology adoption which indicates good dietary diversity. Generally, multiple adoptions of CSA technologies are associated with higher FCS relative to single or non-adoption of CSA technologies. Similarly, adopters recorded higher outcomes than non-adopters of CSA technologies. In terms of the single adopters, SRM adoption is associated with higher FCS on average than mineral fertilizer adoption. However, the application of mineral fertilizer is associated with higher consumption per AEU than SRM adoption. Based on the survey year, SRM adoption increase FCS from 57 in 2013 to 65 in 2018 while mineral fertilizer use resulted in a marginal decline from 61 in 2013 to 59 in 2018. Consumption per AEU tripled with the adoption of SRM varieties between 2013 to 2018. Multiple adoptions of SRM varieties and mineral fertilizers marginally reduced FCS from 64 in 2013 to 61 in 2018 but increased consumption per AEU from 47 in 2013 to 87 in 2018. The findings are indicative and not causality is given that there are both observed and unobserved factors that may be driving the farm and welfare outcomes. In the subsequent section, we control for other characteristics that may drive adoption and the outcomes.

Figure 3 shows the yield effects per the adoption category of CSA technologies and the year of the survey. Generally, adopters of CSA technologies recorded higher yield outcomes than non-adopters of CSA technologies. Similarly, joint adoption of SRM varieties and mineral fertilizer is associated with higher yield than single or non-adoption of CSA packages. In terms of year disaggregation, maize yield declined from 1.5 tons/ha in 2013 to 0.99 tons/ha in 2018. Mineral fertilizer is associated with a marginal decline in maize yield from 1.2 to 1.1 tons/ha. In contrast, the adoption of SRM is associated with a marginal increase in maize yield from 1.1 tons/ha in 2013 to 1.2 tons/ha in 2018. These findings are indicative and not causality.

4 | RESULTS AND DISCUSSION

4.1 | Determinants of adoption of SRM varieties and mineral fertilizer

We report the marginal effects of the MNLS in Equation 2 (Table 2) while the coefficient is reported in Table S3 in the Appendix S1. The results indicate that marginal effects differ significantly across technology choices. The Wald test suggests that the explanatory variables included in the first stage selection model provide a good explanation for the choice of CSA technologies. The Mundlak and instrumental variable significantly explain the choice of CSA technologies. The result suggests that failure to account for endogeneity and unobserved heterogeneity will lead to a biased estimate of CSA technology choice on yield and welfare outcomes. Adoption of SRM variety only (SRM_1FERT_0) is significantly influenced by row planting, the experience of erosion on farmland, and sex-disaggregated leave-out-mean of extension access. Mineral fertilizer adoption only (SRM_0FERT_1) is significantly influenced by the sex of household head and row planting while the joint adoption of SRM variety and mineral fertilizer (SRM_1FERT_1) is significantly influenced by the sex of household head, row planting, risk, the slope of farmland, access to improved seed, age, distance to farm plot, access to extension, and sex-disaggregated leave-out-mean of extension access.

The age of respondents has a negative association with the probability of joint adoption of both SRM varieties and mineral fertilizer (SRM_1FERT_1). An additional increase in the age of a farmer decreases the probability of joint adoption of SRM varieties and mineral fertilizer (SRM_1FERT_1) by 19%. This suggests that younger farmers are more likely to adopt a combination of SRM varieties and mineral fertilizers (SRM_1FERT_1). Consistent with the findings of Adams et al. (2021) the business-mindedness of many youths in agriculture drives them into approaching

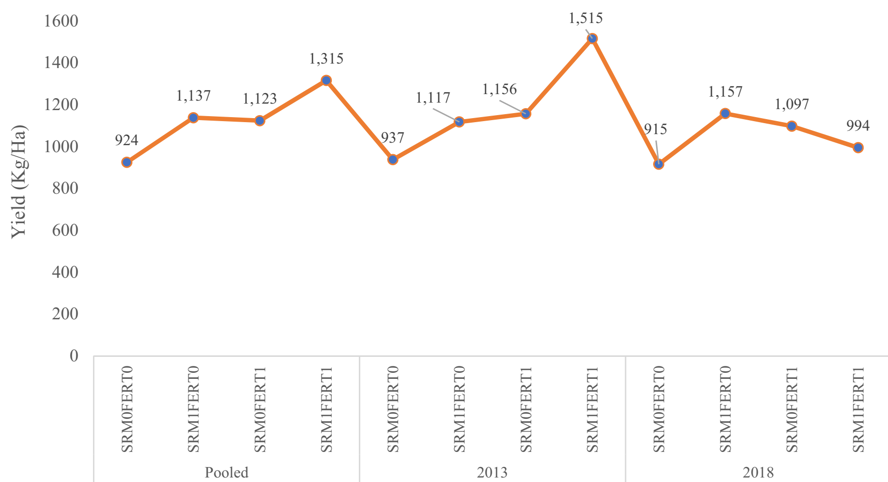


FIGURE 3 Yield effect per adoption category and year of survey

TABLE 2 Marginal effect of adoption of CSA technologies

Variables	SRM_1FERT_0 Coefficient	SRM_1FERT_0 Robust Std. error	SRM_0FERT_1 Coefficient	SRM_0FERT_1 Robust Std. error	SRM_1FERT_1 Coefficient	SRM_1FERT_1 Robust Std. error
Sex of household head (1 = male)	−0.076	0.047	0.291**	0.142	−0.121**	0.052
Marital status of head (1 = married)	−0.028	0.038	0.069	0.101	−0.017	0.038
Model farmer (1 = yes)	−0.026	0.028	−0.010	0.079	−0.040	0.040
Nativity status (1 = native)	−0.037	0.025	0.063	0.084	−0.037	0.035
Farmland inherited (1 = yes)	−0.046	0.049	−0.114	0.088	0.011	0.035
Practice row planting (1 = yes)	−0.067*	0.037	0.220**	0.109	−0.094*	0.051
Own bicycle (1 = yes)	0.033	0.028	−0.091	0.072	0.015	0.029
Own a sprayer (1 = yes)	−0.044	0.035	0.109	0.081	−0.045	0.032
Slope of farmland (1 = slope)	0.034	0.032	0.109	0.074	−0.074**	0.035
Risk (1 = highly impatient)	0.401***	0.070	−0.127	0.125	0.279***	0.048
Experience erosion on farmland (1 = yes)	0.041	0.038	0.116	0.092	−0.057	0.038
Averse to risk (1 = yes)	0.014	0.028	0.020	0.065	−0.031	0.027
Access to improved seed (1 = yes)	−0.052	0.034	−0.029	0.081	−0.054*	0.028
Log of age of household head (years)	−0.060	0.057	−0.217	0.171	−0.192***	0.066
Log of years of education (years)	−0.012	0.015	−0.051	0.032	0.003	0.013
Log of distance to farmland (km)	0.016	0.016	0.039	0.036	−0.019*	0.011
Extension officer visit farmer (1 = yes)	0.024	0.021	0.041	0.041	0.032*	0.019
Leave-out-mean of STM seed and extension access	0.124***	0.029	0.064	0.120	0.207***	0.034
Mundlak variables	Yes		Yes		Yes	
Constant	−10.617**	4.582	1.015	2.785	−10.346	5.275
Joint significance of instrumental variable	8.04**					
Joint significance of time-varying covariates	106.00***					
Wald chi^2 (99)	1338.00***					
Observations	869					

Note: The reference category is non-adoption (SRM_0FERT_0). SRM_1FERT_0—only SRM variety; SRM_0FERT_1—only mineral fertilizer; SRM_1FERT_1—SRM variety and mineral fertilizer; The Mundlak device (mean of the time-varying explanatory variables) was incorporated in the estimation but not reported in the interest of brevity; Significance at 10%, 5%, and 1% are indicated by *, **, and ***, respectively.

Source: Author's computation based on IITA-IFPRI panel survey, 2018.

farming as a business rather than a living leading to the adoption of agricultural technologies.

The result shows that relative to female-headed households, male household heads are 29% more likely to adopt mineral fertilizer. On the contrary, females are 12% more likely to combine the adoption of both Striga-tolerant maize variety and mineral fertilizers. Martey et al. (2020) emphasize production resource-constrains as a limiting factor impeding females' uptake of CSA technologies. However, crop intensification could be the plausible mechanism via which females jointly adopt SRM variety and mineral fertilizer to cope with their limited land access for agricultural production. The association between row planting and CSA technology adoption is mixed. Farmers who plant in rows are 7% less likely to adopt SRM varieties compared to other planting methods. Similarly, row plating is associated with a 9% decrease in the combined adoption of SRM variety and mineral fertilizer compared to non-adopters. Such negative association contradicts our a priori expectation, however, row planting as an improved land management technique is complex and demands high management skills (Gollin et al., 2005; Vandercasteelen et al., 2016). Row planting carried out effectively in a farmer-managed plot with a traditional variety has the potential for yield improvement given that it allows for effective weed control and good aeration. Martey et al. (2020) find that row planting has a higher yield effect than improved maize variety. In contrast, row planting increases the adoption of mineral fertilizer only. The finding is consistent with literature that indicates that row planting increases the likelihood of mineral fertilizer adoption (Donkor & Owusu, 2019). Row planting ensures a more effective and efficient way of fertilizer application whiles minimizing losses.

The slope of farmland decreases the likelihood of adopting both SRM varieties and mineral fertilizer (SRM_1FERT_1) by 7%. On the contrary, studies from Ghana and South Africa on the determinants of ISFM adoption and adoption of agroforestry technologies show that households with sloped farmlands have a higher likelihood of adopting fertilizer and agroforestry technologies (Martey & Kuwornu, 2021; Zerihun et al., 2014). However, the result is consistent within the framework of rationality where farmers will be reluctant to invest in land productivity, especially for sloped farmlands that are more prone to erosion and soil nutrient loss relative to flat farmlands. The results suggest that farmers care much about the cost of investment relative to the long-term gains. Farmers who are highly impatient are more likely (40%) to adopt only SRM varieties (SRM_1FERT_0) and joint adoption of both SRM varieties and mineral fertilizer (SRM_1FERT_1; 28%) compared to farmers who are patient in their expectations. Highly impatient farmers have high expectations of returns from CSA adoption in the short term and thus are more likely to swiftly adopt practices that control Striga weed and improve land productivity.

Contrary to expectation, farmers who have access to improved seeds are 5% less likely to adopt both SRM variety and mineral fertilizer (SRM_1FERT_1). In a separate study by Martey et al. (2020), they find that access to DTMVs is associated with a 36% chance of adopting DTMVs. Often, agricultural technologies come as a package and incomplete access to these technologies discourage their adoption. In addition, farmers may have access in terms of distance to the nearest input outlets but may not have the purchasing power to purchase the seed inputs. Similarly, the seed inputs may not be available when needed thus reducing the probability of adoption. A unit increase in the distance from the homestead to the farm plot decreases the probability of adopting both SRM varieties and mineral fertilizer (SRM_1FERT_1) by 19%. The distance to the farm is critical to the adoption decision of farmers. Farther farms may serve as a disincentive for farmers to transport farm inputs to their farms. Under such circumstances, farmers may less likely to adopt CSA technologies due to the high cost of investment both in terms of labour and transportation cost. The result is consistent with Ogada et al. (2010) who find that distance to farmer farms reduces the adoption decision of manure by farmers. Similarly, Martey and Kuwornu (2021) find that distance to farmer's field reduces the adoption of green manure by 25%.

The probability of adopting only STM varieties (SRM_1FERT_0) and joint adoption of SRM varieties and mineral fertilizer (SRM_1FERT_1) is positively related to access to SRM seed and extension services. Extension access serves as a major source of information on improved technologies in many parts of Africa and other developing nations. Such information creates farmer awareness of existing and new agricultural technologies leading to adoption and investment in these technologies. Our finding is consistent with past studies that show that farmers are more likely to adopt agricultural technologies and practices if they have access to extension services (Fentie & Beyene, 2019; Khonje et al., 2018; Martey & Kuwornu, 2021; Zeng et al., 2017).

4.2 | Farm and welfare effect of CSA technologies adoption

4.2.1 | Yield effects of CSA adoption

We report the effects of the adoption of CSA technologies on yield, HDDS, FCS, and consumption per AEU under actual and counterfactual conditions after controlling for selection bias in Table 3. In the interest of brevity, the second-stage regression is not discussed but is reported in the Tables S4–S7. The estimation of the effect of CSA technologies adoption under both conditional and unconditional average effects is based on the predicted outcomes from MESR.

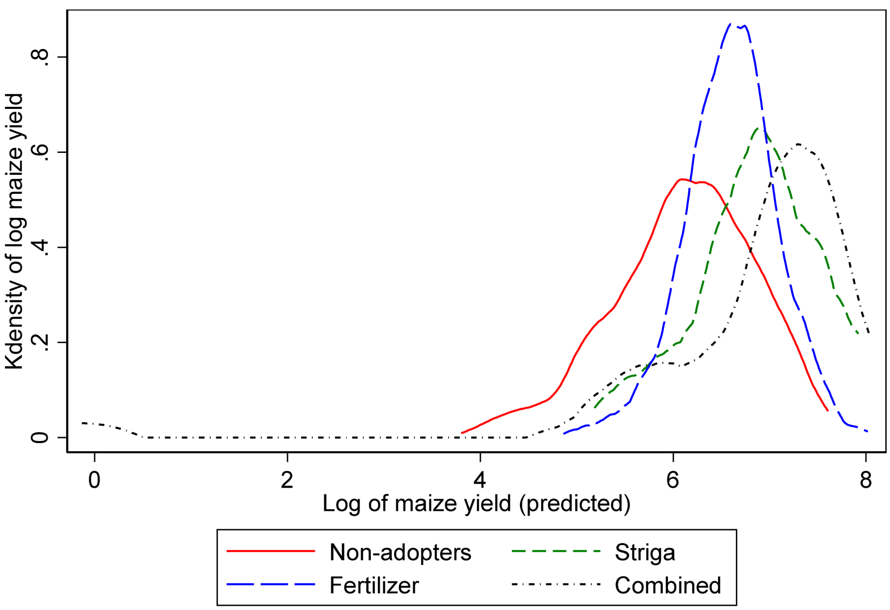
Table 3 shows the average effects of CSA technologies adoption on yield, HDDS, FCS, and consumption per AEU after controlling for selection bias due to observed and unobserved factors. The results suggest that farmers who adopted CSA technologies would have obtained lower benefits had they not adopted. Column 3 of Table 3 shows that the adoption of SRM varieties and mineral fertilizer impact positively on maize yield. Joint adoption of SRM varieties and mineral fertilizer (SRM_1FERT_1) had the highest yield effect (872 kg/ha) followed by SRM varieties only (SRM_1FERT_0; 545 kg/ha) and mineral fertilizer only (SRM_0FERT_1) (402 kg/ha). The combined significantly highest effect of the adoption of SRM varieties and mineral fertilizer on maize yield suggests a complementarity effect. The result is consistent with previous studies that find a complementary association between crop varieties and mineral fertilizer (Jaleta et al., 2016; Kassie et al., 2018). Our result is consistent with the findings of Khonje et al. (2015) in eastern Zambia. They find that the adoption of improved varieties and conservation agriculture

TABLE 3 MESR-based average treatment effects of adoption of CSAs on household welfare

		Adoption status		Average treatment effect
		Adopting (j = 1, 2, 3)	Non-adopting (j = 0)	
Outcomes	**Technology choice (j)**	**(1)**	**(2)**	**(3) = (1)−(2)**
Yield (kg/ha)	SRM_1 $FERT_0$	1150 (123)	605 (78)	545*** (120)
	SRM_0 $FERT_1$	819 (21)	417 (17)	402*** (28)
	SRM_1 $FERT_1$	1326 (128)	455 (51)	872*** (131)
HHDS	SRM_1 $FERT_0$	719 (0.18)	7.10 (0.09)	0.08 (0.18)
	SRM_0 $FERT_1$	716 (0.02)	7.10 (0.02)	0.06* (0.03)
	SRM_1 $FERT_1$	726 (0.16)	7.08 (0.07)	0.18 (0.10)
FCS	SRM_1 $FERT_0$	68.56 (3.39)	47.12 (3.13)	21.45*** (4.37)
	SRM_0 $FERT_1$	57.88 (0.66)	48.77 (0.97)	9.12*** (1.13)
	SRM_1 $FERT_1$	64.46 (2.39)	47.81 (2.72)	16.65*** (3.89)
Consumption per AEU	SRM_1 $FERT_0$	76.50 (21.45)	26.49 (3.20)	50.01*** (4.37)
	SRM_0 $FERT_1$	53.34 (1.73)	23.58 (0.65)	29.75*** (1.92)
	SRM_1 $FERT_1$	62.48 (12.69)	24.28 (1.97)	38.19*** (13.18)

Note: The reference category is non-adoption (SRM_0FERT_0). SRM_1FERT_0—only SRM variety; SRM_0FERT_1—only mineral fertilizer; SRM_1FERT_1—SRM variety and mineral fertilizer. The Mundlak device (mean of the time-varying explanatory variables) was incorporated in the estimation but not reported in the interest of brevity. Significance at 10%, 5%, and 1% are indicated by *, **, and ***, respectively.

Source: Author's computation based on IITA-IFPRI panel survey, 2018.



Source: IFPRI-IITA Panel Survey, 2018

FIGURE 4 Kernel density distribution of maize yield

increases maize yield by 605 kg/ha. Concerning the effect of mineral fertilizer, several studies have reported an increase in yield due to mineral fertilizer adoption (Biazin & Stroosnijder, 2012; Liverpool-Tasie et al., 2017; Martey et al., 2019). However, Habtemariam et al. (2019) demonstrated that fertilizer dozing technology leads to a considerable increase in crop yield and consequently reduces food insecurity in farming communities of Tanzania.

Figure 4 illustrates the yield effects of the adoption of CSA technologies using kernel densities of predicted maize yield distributions by adoption status. The kernel density distribution of maize yield (log) for both SRM varieties and mineral fertilizer adopters (SRM_1FERT_1) is positioned to the far right of all other technology choices. The results further demonstrate the positive impact of the joint adoption of CSA technologies on maize yield thus the need to intensify multiple agricultural technologies without necessarily increasing plot size.

4.2.2 | Food security effects of CSA adoption

With reference to the food security outcomes, the results show that on average, adopters would have recorded low HDDS, FCS, and consumption per AEU from the three technology choices had they not adopted them (Table 3). The results indicate that the adoption of CSA technologies is associated with an increase in food security. In reference to HDDS, adopters of only mineral fertilizer (SRM_0FERT_1) experienced a 0.06 increase in HDDS. However, adopters of both SRM varieties and mineral fertilizer (SRM_1FERT_1) and only SRM varieties (SRM_1FERT_0) had no significant effect on HDDS. Our results suggest that farm households who adopt mineral fertilizer only are more likely to experience improvement in the diversity of their diets. Figure 5 shows that the kernel distribution of HDDS (log) for the joint adoption of SRM varieties and mineral fertilizer (SRM_1FERT_1) and only STM varieties (SRM_1FERT_0) are positioned furthest to the right of all the other technology choices although not significant. Despite the food security gains in mineral fertilizer, the statistical significance of the result is weak which indicates that the adoption of CSA is weakly associated with HDDS.

For FCS, the results show that, on average, the adoption of CSA technologies is associated with increased FCS. Adopters of only SRM varieties (STM_1FERT_0) recorded the highest FCS effect (21) followed by combined adoption of both SRM varieties and mineral fertilizer (SRM_1FERT_1) (17), and mineral fertilizer only (SRM_0FERT_1) (9). The results show that the adoption of CSA technologies is more likely to increase household energy sufficiency (caloric intake). From the analysis, we conclude that improvement in household energy sufficiency (measured by FCS) is more evident among adopters of SRM varieties.

We complement our findings with the kernel densities of predicted FCS distributions by adoption status (Figure 6). The figure shows that the kernel distribution of FCS (log) for only SRM varieties (SRM_1FERT_0) lies furthest to the right of all the other technology choices followed by the kernel distribution of the joint adoption of SRM varieties and mineral fertilizer (SRM_1FERT_1). The results suggest that development interventions that address food insecurity challenges must focus on promoting SRM varieties. The effect of SRM varieties in improving food security is consistent with Adams et al. (2021) findings that recognize maize as critical to meeting Ghana's food and dietary needs. However, maize production is constrained by low soil fertility (Mwinuka et al., 2017), therefore such constraints demand the use of soil fertility improvement technologies such as mineral fertilizer to raise productivity and food security.

Consistent with the FCS results, we find that adopters of only SRM varieties (SRM_1FERT_0) recorded the highest consumption per AEU effect (50 kg) followed by combined adoption of both SRM varieties and mineral fertilizer (SRM_1FERT_1; 38 kg), and mineral fertilizer only (SRM_0FERT_1; 30 kg). Our result implies that SRM varieties are positively associated with an increase in maize consumption. The plausible mechanism is via an increase in maize yield. This indicates that an increase in maize yield translates to an increase in maize consumption. The consumption gains are clearly shown using kernel

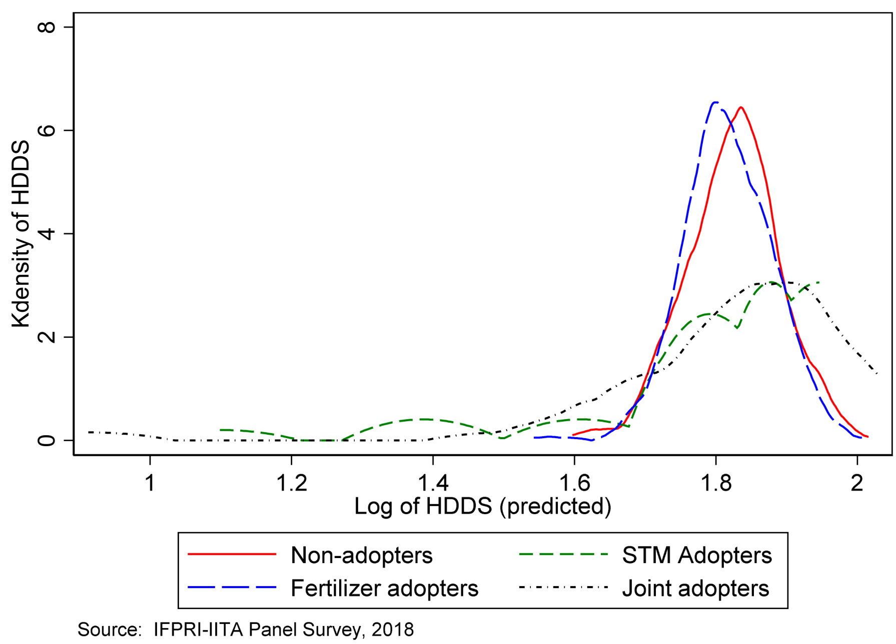


FIGURE 5 Kernel density distribution of HDDS

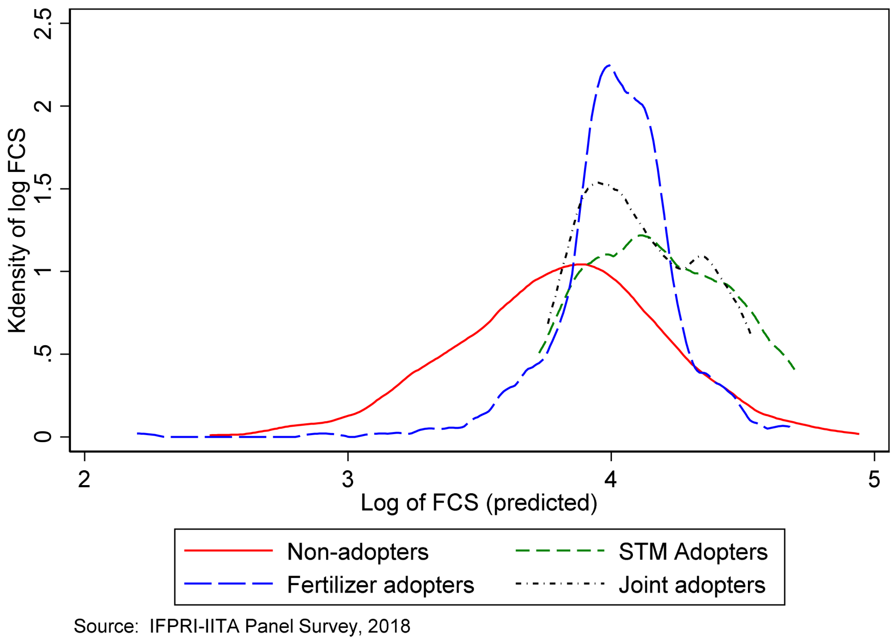


FIGURE 6 Kernel density distribution of FCS

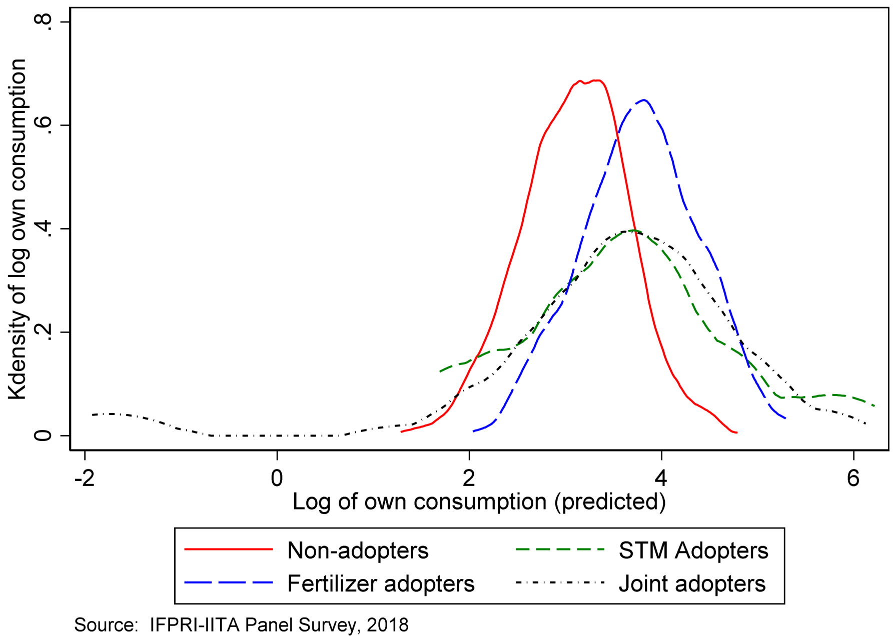


FIGURE 7 Kernel density distribution of consumption

densities of predicted consumption per AUE distributions (Figure 7). Kernel density of consumption per AEU (log) for only SRM varieties adoption lies furthest to the right of all other technology choices—SRM_1FERT_1, SRM_0FERT_1, and nonadopters (SRM_0FERT_0). The positive effect of improved maize variety adoption is consistent with the findings of Fentie and Beyene (2019) and Bezu et al. (2014) who find a positive effect of improved maize adoption on own consumption per AEU in Malawi and Ethiopia, respectively. In a separate study, Manda et al. (2018) show that the adoption of improved maize varieties leads to U.S.$43 increases in food expenditure.

4.3 | Robustness checks

Table 4 reports the results from the Lewbel 2SLS panel regression that combines both internally generated and external instruments to control for endogeneity in the choices of SRM varieties and mineral fertilizers. Consistent with the MESR results and after accounting for endogeneity, the adoption of CSA technologies impacts positively yield, FCS, and consumption per AEU. Comparatively, the magnitude of the effects of CSA technologies based on the Lewbel 2SLS is consistently higher than the MESR-based estimate except for adopters of only

STM varieties where the MESR-based estimates for FCS and consumption per AEU is higher than the Lewbel 2SLS-based estimates. Overall, our result is robust in terms of the positive effect of CSA technologies adoption on maize yield, FCS, and consumption per AEU. Farm households in Ghana are more likely to experience higher maize yields and food security from multiple adoptions of CSA technologies.

5 | CONCLUSION

Multiple agricultural technologies' adoption effects on household welfare have long been studied especially within developing contexts. However, there is a paucity of information on how the combination of CSA technologies such as SRM varieties and mineral fertilizer jointly impact maize yield and food security. This study uses a farm-level panel data and a multinomial endogenous switching regression model to evaluate the adoption and welfare impacts of CSA technologies in Ghana. The MESR model corrects for selection bias and endogeneity due to observed and unobserved heterogeneity.

Results show that the adoption of CSA technologies significantly increases maize yield, FCS, and food consumption per AEU. Farm households achieved the maximum yield when farmers adopt both SRM varieties and mineral fertilizer as compared to adopting only SRM varieties or only mineral fertilizer. However, we observed that the adoption of only SRM varieties is significantly

TABLE 4 Lewbel 2SLS estimates of CSA and welfare

	(1)	(2)	(3)	(4)
Variables	**Yield**	**Log (HDDS)**	**Log (FCS)**	**Log (consumption)**
Panel A: SRM variety				
SRM_1FERT_0	630.646** (305.617)	0.610 (0.433)	17.544** (7.578)	44.596** (20.231)
Controls	Yes	Yes	Yes	Yes
First stage				
Extension access	0.603*** (0.100)	0.611*** (0.100)	0.604*** (0.968)	0.605*** (0.098)
Diagnostic tests				
Underidentification test	29.09***	29.12***	30.14***	30.15***
Weak identification test[a]	36.56	37.16	38.95	38.48
Observations	845	845	872	872
Panel B: Mineral fertilizer				
SRM_0FERT_1	959.341** (389.307)	0.600 (0.492)	19.976** (9.037)	54.910** (27.172)
Controls	Yes	Yes	Yes	Yes
First stage				
Extension access	0.531*** (0.113)	0.531*** (0.113)	0.531*** (0.113)	0.491*** (0.115)
Diagnostic tests				
Underidentification test	18.20***	18.20***	18.20***	15.57***
Weak identification test	21.88	21.88	21.88	18.19
Observations	872	872	872	872
Panel C: STM and mineral fertilizer				
SRM_1FERT_1	1104.099** (538.173)	0.492 (0.394)	25.487** (12.824)	44.122** (20.635)
Controls	Yes	Yes	Yes	Yes
First stage				
Extension access	0.407*** (0.105	0.648*** (0.107)	0.397*** (0.105)	0.611*** (0.109)
Diagnostic tests				
Underidentification test	14.75***	28.29***	13.80***	25.22***
Weak identification test	14.95	36.40	14.30	31.49
Observations	847	872	872	872

Note: Robust standard errors in parentheses; $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

[a]The weak identification test is based on Kleibergen–Paap rk Wald F statistic.

associated with higher food security outcomes (FCS and food consumption per AEU) than adopting only mineral fertilizer and joint adoption of SRM varieties and mineral fertilizer. Adoption of only mineral fertilizer had a modest effect on HDDS compared to the adoption of only SRM varieties and the adoption of both SRM varieties and mineral fertilizer which had no significant effect on HDDS. The result suggests that the gains in CSA technologies adoption can be consolidated and sustained if the promotion of CSA practices considers important factors such as sex, age of farmer, row planting, the slope of farmland, risk perception, access to improved seed, distance to farm plot, and access to extension services.

Our findings have several important implications in Ghana. The results imply that the promotion of CSA technologies through agricultural extension agents and making it accessible for wider adoption among smallholder farmers could increase maize productivity and household food security. The yield and welfare effects can be sustained through the provision of technical support services from the extension. However, the extension support services must be adequately supported with logistics to ensure effective extension delivery services. Second, the adoption of multiple CSA technologies (SRM varieties and mineral fertilizer) may be associated with high cost, therefore, in the presence of financial constraints, farmers can be encouraged to adopt only SRM varieties complemented with good farm management practices to enhance household food security outcomes.

A cost-effectiveness analysis of CSA technologies intervention will complement the findings from the impact evaluation. Currently, the study lacks such analysis due to limited data on the cost of implementing CSA interventions in Ghana. Secondly, the study may not have accounted for the dynamic effect of adoption on maize yield and welfare outcomes due to the short period between the baseline and endline survey periods. Therefore, our results only capture the short-term effects of CSA technologies. Finally, the study will benefit more from a heterogeneity analysis that considers household's different levels of crop commercialization and market orientation. Therefore, future research should consider using a longitudinal panel dataset to address these research gaps.

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CONFLICT OF INTEREST

The authors have stated explicitly that there are no conflicts of interest in connection with this article.

DATA AVAILABILITY STATEMENT

Data available on request due to privacy/ethical restrictions.

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ENDNOTES

[1] Climate-smart agriculture is defined as the agriculture that sustainably increases productivity, enhances resilience (adaptation), reduces/removes GHGs (mitigation) where possible, and enhances achievement of national food security and development goals (FAO, 2013). The three pillars of CSA are productivity, adaptation, and mitigation. Examples of specific CSA interventions include soil management, drought-tolerant maize, striga resistance maize, carbon finance to restore crop fields, waste-reducing rice thresher, rainfall forecasts, and incentive system for low-carbon agriculture.

[2] According to Adu et al. (2021), the three major production constraints that cause production losses in SSA are poor soils (44%), weeds (19%), and drought (18%).

[3] This is a specific class of panel endogenous switching regression model proposed by Malikov and Kumbhakar (2014). The MESR is applicable in this case due to the polychotomous nature of the choice of GAPs.

[4] There are several methods for correcting for selectivity bias which includes Lee (1983), Dubin and McFadden (1984), Schmertmann (1994), and Bourguignon et al. (2007). Refer to Abdul-Rahaman and Abdulai (2020) for detailed analysis of the

strengths and weaknesses of the various methods of correcting for selectivity bias.

5 The IMR is computed as $\widehat{\lambda}_{jit} = \sum_{k \neq j}^{j} \rho_j \left[\frac{\widehat{p}_{ki} \ln(\widehat{p}_{ki})}{1 - \widehat{p}_{ki}} + \ln(\widehat{p}_{jit}) \right]$ where ρ is the correlation between ε_{jit} and μ_{jit}. The standard errors in Equation (3) were bootstrapped to account for the heteroscedasticity resulting from the generated regressors due to the two-stage estimation procedure.

6 A falsification test certifies the admissibility of the selection instrument as a valid instrument: if a variable is an appropriate selection instrument, it will influence the adoption decision, but it will not influence the welfare outcome variables. Our results indicated that access to information on factor inputs is not directly related to land productivity and agricultural income. Hence, this variable was used as the instrument.

7 The ATT is computed based on the post-estimation prediction of the actual and counterfactual expected value of the outcomes for a household that adopt technology j after estimating the MESR in Equation (5).

8 The Lewbel 2SLS method requires that the exclusion restriction is satisfied by creating instruments that are the product between the mean centered exogenous variables of the model and the residuals from the first stage regression of the endogenous variable on all the exogenous regressors of the model. The model is identified by having regressors that are uncorrelated with the product of the heteroskedastic errors.

9 The definition of an EA was based on the same classifications and boundaries as used in Ghana's Population and Housing Census and the country's Living Standards Survey (GLSS; Ragasa et al., 2014).

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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