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Welfare impacts of climate-smart agriculture in Ghana: Does row planting and drought-tolerant maize varieties matter?

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ABSTRACT

This study provides new evidence of the impact of climate-smart agriculture (CSA) – row planting and drought-tolerant maize varieties - on farm and welfare outcomes by estimating a multinomial endogenous switching regression model that corrects for selection bias and farmer heterogeneity in CSA choice. Application of our model to panel observations of 438 households in Ghana show that adoption of CSA increases both yield and intensity of maize commercialization but negatively affect own consumption. Specifically, the magnitude of the impact is relatively higher for adopters of row planting relative to adopters of drought-tolerant maize seeds. These results suggest the need for development practitioners to increase awareness and emphasize the importance of row planting as a key component of climate-smart agriculture.

1. Introduction

In Africa, 70 % of the population are smallholder farmers who cultivate an average plot size of less than 2 ha (Alliance for a Green Revolution in Africa, AGRA, 2017). These farmers especially those in Sub-Saharan Africa (SSA) rely on poor and unsustainable farming practices leading to poor soil fertility (Grabowski et al., 2016) with subsequent decline in crop yield, and high incidence of food insecurity and poverty (Kassie et al., 2015; Fisher et al., 2015). According to Hansen et al. (2019), the livelihoods of agricultural households are mostly affected by these constraints since they operate in environments characterised by high risks and weak institutions. However, the agricultural sector is expected to lead the African transformation process given that the sector has considerable untapped irrigation, vast uncultivated land for agricultural production, and a huge potential to address the increasing demand for food and nutrition security due to population growth, and issues relating to poverty (Fuglie, 2018; AGRA, 2017).

Despite the large share of Africans involved in agriculture and the potential of becoming food self-sufficient, the region is inundated with high import bill which stands at US$35 billion, and is estimated to rise to US$110 billion by 2025 (Adesina, 2017). To close this gap and achieve the sustainable development goal 2 which seeks to end hunger, achieve food security and improved nutrition and promote sustainable agriculture; development partners and African governments have implemented projects and programs such as soil heath projects, conservation agriculture, agricultural value chain mentorship program, fertilizer subsidy programs among others (Brüntrup, 2011). These projects and programs are aimed at increasing land and labour productivity to achieve sustainable food production. In Ghana, the government of Ghana has launched the “planting for food and jobs program” as a strategy to build the capacity of farmers and increase their access to quality certified seeds and fertilizers through a private sector led marketing framework. The program also seeks to build the capacity of extension agents and adequately resource them to train farmers on good agronomic practices and commercialization of outputs over an e-agriculture platform (Ministry of Food and Agriculture, 2017). Improved maize variety is one of the target crops for the program since it is widely cultivated by household for both consumption and commercialization. In view of this, any complementary support to the maize sub-sector will have a wide ripple effect on incomes and food security.

To increase yield and sustain household income in the midst of climate change and other related risks, development practitioners argue for the adoption of climate-smart agriculture (CSA). For example, drought-tolerant maize (DTM) seed is being promoted among resource-poor farmers to lower the risks of crop failure resulting from among others, low and uneven rainfall pattern in different agro-ecological zones (Fisher et al., 2015). Row planting, a component of climate smart agricultural (CSA) also has the potential of increasing agricultural productivity and incomes as well as building resilience against climate

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shocks (Fantie and Beyene, 2019; Teklewold et al., 2017).

Several studies have evaluated the impact of single agricultural technology use on welfare of farm households (Zeng et al., 2017; Abdulai, 2016; Asfaw et al., 2016; Jaleta et al., 2016; Khonje et al., 2015; Bezu et al., 2014). Issahaku and Abdulai (2019) find that adoption of climate smart practices positively and significantly impacts on food and nutrition security. Abdulai and Huffman (2014) establish that adoption of soil and water conservation measures impact positively on yields and net farm revenues. Some studies (Ng'ombe et al., 2017; Teklewold and Mekonnen, 2017; Manda et al., 2016) have used cross-sectional data to analyse the economic impact of multiple technology adoption. Such results are very insightful but unable to deal with econometric issues (unobserved heterogeneity due to time-varying characteristics) associated with the use of cross-section data (Michler et al., 2019). However, panel data is able to produce a more accurate inference of model parameters, accounts for dynamism in adoption (uncovering dynamic relationships), and overcome measurement errors that may bias parameter estimates (Hsiao, 2007). Using panel data, Khonje et al. (2018) find that adopting improved seed and conservation agricultural practices impact positively on maize yield and income but negatively on poverty. Despite the numerous studies on the economic and welfare impact of improved maize varieties in SSA, there is limited evidence on the welfare impact of row planting as a complement to improved seed. A more recent study that uses cross-sectional data show that row planting impacts positively on per capita consumption and crop income per hectare (Fentie and Beyene, 2019). However, their study is limited in terms of identifying how other technologies complement row planting.

This study contributes to the literature by identifying the relevant factors influencing the adoption of row planting and improved seed. Secondly, the study adds to the literature on agricultural innovation systems by using a panel data and Multinomial Endogenous Switching Regression (MESR) model to establish how row planting and DTM variety impacts on yield, intensity of maize commercialization and own consumption per adult equivalent unit (AEU). Finally, the study demonstrates the effectiveness of row planting as a mechanism for increasing resilience in farming systems.

The rest of the paper is organized as follows. Section 2 describes the theoretical and empirical strategy employed by the study while section 3 discusses and describes the data. Section 4 presents the empirical results and discussion with section 5 highlighting the main conclusions and implications of the study.

2. Theoretical framework and empirical strategy

The decision to use CSA practice is a behavioural response thus modelled within the random utility framework (Kassie et al., 2018; Ali and Abdulai, 2010) where a farmer chooses a component of the CSA practices that increase utility. Following the argument of Pannell et al. (2014), we consider a household's decision to adopt CSA practices in a reference year a constrained optimization problem where the polychotomous adoption decision depends on a number of factors including available information, relative costs and benefits of CSA, and socio-economic conditions. A household may decide to adopt a single or a combination of the CSA practices such as DTM variety (IMP), row planting (ROW), and a combination of row planting and DTM variety (IMPROW).

Given that farmers make production decisions regarding the optimum input choice, those decisions can be modelled based on expected profit. A farmer will select any of the choice sets (of CSA practices) if the expected profit from adoption is higher than the expected profit from non-adoption as follows:

$$\pi_{it}^{*CSA} = p_{it} Q_{it}^{*CSA} - \sum_{j=1}^{J} \omega_{jit} Z_{jit}^{*CSA} > \pi_{it}^{*NCSA} = p_{it} Q_{it}^{*NCSA} - \sum_{j=1}^{J} \omega_{jit} Z_{jit}^{*NCSA} \tag{1}$$

where Q_{it}^{CSA} and Q_{it}^{NCSA} are the respective vector of outputs for CSA and non-CSA (NCSA) farmers; p_{it} is a vector of output prices which is considered to be same for both category of farmers; ω_{jit} and Z_{it} are vectors of input prices and inputs respectively.

We expect that the welfare pathway effect of CSA adoption will be realized through an increase in crop yield. Adoption of CSA practice will lead to an increase in crop yield *ceteris paribus* which will likely increase market participation (intensity of commercialization) assuming that market conditions are favourable (Barrett, 2008). With increased market participation, own consumption is likely to reduce due to increased sales. If the outcome variables are a linear function of the adoption decision, along with a vector of other explanatory variables X, and regional dummy variables D_v, then the following equation holds:

$$Y_{jit} = \vartheta X_{jit} + \beta T_{jit} + D_v + c_i + \varepsilon_{it} \tag{2}$$

where Y_{it} is the outcome variable, T_{it} represents an indicator variable for CSA adoption, ϑ and β are vectors of parameters to be estimated, c_i is unobserved time-constant factors, and ε_{it} is a mean zero, identically and independently distributed (iid) random error assumed to be uncorrelated with the explanatory variables. The parameter β accurately measures the impact of adoption on the outcome variable under the condition that farmers are randomly assigned to treatment and non-treatment groups (Faltermeier and Abdulai, 2009). Direct estimation of β will be biased given that the adoption of CSA practices was non-random. Secondly, farmers may self-select and the decisions to adopt are likely to be influenced by unobserved human (motivation, entrepreneurial ability, preferences, innovative ability, etc.) and farm characteristics (average soil quality or fertility) and observed factors that may be correlated with the outcome variables (Pannell et al., 2014; Marenya and Barrett, 2009). For example, risk averse farmers may be more likely to adopt a single CSA practice while risk-lovers may be more likely to adopt combinations of CSA practices. The differences in the level of adoption may have heterogeneous effect on the outcome. In view of the above challenges, there is a need to address self-selection and unobserved heterogeneity associated with economic evaluations of the non-random adoption of innovations such as CSA practices.

To address the problem of selection bias, several studies (Martey et al., 2019; Khonje et al., 2015; Kassie et al., 2011) used the propensity score matching (PSM) method. According to Jaleta et al. (2016) and Abdulai (2016), PSM is unable to correct for selection bias attributable to unobserved factors. The use of fixed effects (FE) model controls for the endogeneity problem (arising from unobserved heterogeneity) by eliminating the effects of time-constant factors. Employing the FE model on the adoption of CSA practices may be problematic based on the assumption that the model difference out the correlation between the individual effects and the explanatory variables. However, some studies have argued that this is a strict assumption since the economic outcome of CSA can be heterogeneous as a result of both observed and unobserved characteristics (Kassie et al., 2018; Suri, 2011). The FE model also assumes that unobserved time-constant variables are the only omitted variables in estimating the use of CSA practices on the outcomes. Suri (2011) argues that this assumption is less likely to hold given that households might move in and out of CSA practices during the period of the panel as a result of changes in unobservable factors that may also affect the outcomes.

We employ the multinomial endogenous switching regression (MESR)[1] to account for selection bias and endogeneity arising from

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

both observed and unobserved heterogeneity. Application of the MESR have several advantages. First, it corrects for the selection bias by computing an inverse Mills ratio (IMR) based on the theory of truncated normal distribution (Malikov and Kumbhakar, 2014; Bourguignon et al., 2007). Second, it enables the construction of counterfactuals based on returns to the characteristics of CSA adopters and non-adopters (Kassie et al., 2017). Third, it allows for an interaction between the CSA technology choice set and the explanatory variables to capture the effect of CSA on a shift of both intercept and slope of the outcome equation (Abdoulaye et al., 2018; Kassie et al., 2017; Di Falco and Veronesi, 2013). Finally, the model identifies the specific choice of CSA practices with the highest outcome effect (Wu and Babcock, 1998).

The MESR is a two-stage simultaneous estimation technique. The first stage models farmers' choice of CSA using a multinomial logit selection (MNLS) equation by accounting for unobserved heterogeneity. The IMRs calculated from the first stage are included in the outcome equation as additional covariates to account for selection bias from time-varying unobserved heterogeneity. The outcome equation is estimated using Ordinary Least Squares (OLS).

2.1. First stage: Multinomial logit selection model

As earlier stated, the first stage estimation of the factors that influence the choice of CSA is modelled within the random utility framework where a farmer i in time t chooses a CSA technology set ($j = 1, \ldots\ldots, 3$) that maximizes expected utility (U_{jit}). A farm household will choose a CSA technology set j if its expected utility is relatively higher than other technology set k i.e. $\rho_{1it} = \max_{k \neq j}(U^*_{kit} - U^*_{jit}) < 0$.

Assuming the utility from choosing a CSA technology set j can be represented by the latent variable U^*_{jit}. Following Khonje et al. (2018), we specify the latent model that describes farmers' CSA adoption behaviour as:

$$U^*_{jit} = \delta_j X_{jit} + \varphi_j \overline{X}_{ji} + \varepsilon_{jit} \text{ where } \varepsilon_{jit} = c_i + \eta_{jit} \tag{3}$$

with

$$U = \begin{cases} 1 \text{ if } U^*_{jit} > \max\limits_{k \neq 1}(U^*_{kit}) \text{ or } \rho_{1it} < 0 \\ \vdots & \forall\ k \neq j \\ J \text{ if } U^*_{jit} > \max\limits_{k \neq j}(U^*_{kit}) \text{ or } \rho_{jit} < 0 \end{cases} \tag{4}$$

where X_{jit} is a vector of observed covariates (demographic, farm characteristics, wealth indicators, access to extension and regional dummies[2] that accounts for temporal and spatial differences in agro-ecology and institution) that affect the probability of choosing a CSA technology set; $\overline{X}_{ji}$ is the mean of all time-varying covariates; δ and φ are vector of parameters to be estimated and c_i and η_{jit} represent the household specific heterogeneity and time-varying unobserved factors or idiosyncratic errors, respectively. A correlation between the unobserved factors and explanatory variables ($E[\eta_{jit}|X_{jit}] \neq 0$) could lead to inconsistent estimate of the MNLS model. Based on the assumption that η_{jit} is independent and identically Gumbel distributed across all CSA choice sets (i.e. the independence of irrelevant alternatives (IIA) hypothesis) (Bourguignon et al., 2007), Eq. (3) leads to a multinomial logit model (Mc-Fadden, 1973) where the probability (P_{jit}) that a farmer i at time t will choose technology j out of J options can be expressed as:

$$P_{jit} = \Pr(\rho_{1it} < 0 X_{jit}) = \frac{\exp(\delta_j X_{jit} + \varphi_j \overline{X}_{ji})}{\sum_{k \neq 1}^{J} \exp(\delta_k X_{kit} + \varphi_k \overline{X}_{ki})} \tag{5}$$

We estimate Eq. (5) using a pooled MNLS model with correction for unobserved heterogeneity using the Mundlak (1978) and Wooldridge (2010) approach where the time-invariant unobserved effect (c_i) is modelled as a linear projection of the means of all time-varying observed explanatory variables ($\overline{X}_{ji}$) as: $c_i = \pi \overline{X}_{ji} + \alpha_i$.

2.2. Second stage: Multinomial endogenous switching regression model (MESR)

The second stage estimates the impacts of CSA choice sets (IMP_0ROW_0—non-adopters as reference category; IMP_1ROW_0—adopters of DTM variety; IMP_0ROW_1—adopters of row planting only; IMP_1ROW_1—adopters of both improved varieties and row planting) on farm level and welfare outcomes. However, the IMP_1ROW_1 category of farmers were dropped due to less data points. The choice of a specific CSA technology leads to a separate outcome equations with the treatment effects (of interest) being a binary comparison of the actual and counterfactual outcomes for CSA adoption and non-adoption. Following Kassie et al. (2018) and Khonje et al. (2018), the outcome equation for each possible regime j with selection bias correction term is specified as:

$$\begin{cases} \text{Regime } 1\text{: } Y_{1it} = \beta_1 M_{1it} + \sigma_1 \hat{\lambda}_{1it} + \vartheta_1 \overline{M}_{1i} + \mu_{1it} \text{ if } U = 1 \\ \vdots & j = 2,\ 3 \\ \text{Regime } J\text{: } Y_{jit} = \beta_j M_{jit} + \sigma_j \hat{\lambda}_{jit} + \vartheta_j \overline{M}_{ji} + \mu_{jit} \text{ if } U = J \end{cases} \tag{6}$$

where Y_{jit} represents the outcome associated with the selected regime $j(j = 0, \ldots., J)$ and observed for all possible combination of CSA practices used, M_{jit} represents a 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), $\hat{\lambda}_{jit}$ is the IMR calculated from the estimated probabilities in Eq. (5).

The inclusion of the IMRs in Eq. (6) leads to a consistent estimate of β_j and ϑ_j using OLS. Given that the second stage outcome model include estimates from the first stage selection model, the standard errors in Eq. (6) are bootstrapped to account for heteroscedasticity (Khonje et al., 2018). Even though Eq. (6) can be identified using non-linearity of the selection model, it is important to observe exclusion restriction (Di Falco, 2014), for. Following previous studies (Khonje et al., 2018; Zeng et al., 2017; Abdulai, 2016; Kassie et al., 2015), we exclude access to extension services (dummy and continuous) and extension contacts from our outcome equations. Agricultural extension agents are the main source of agricultural information regarding new technologies and practices. The only means of causal impact is through adoption of CSA given that farmers will adopt modern technologies when they have adequate information about the benefits. The admissibility of the instrument is established through a simple falsification[3] test proposed by Di Falco et al. (2011). The results confirm that the excluded variables have significant effect on CSA practices but do not significantly influence the outcome variables of non-adopters (Table A1).

2.3. Estimation of average treatment effects on the treated (ATT)

The treatment effect on the treated due to the adoption of CSA is computed by comparing the expected values of outcomes of adopters and non-adopters of CSA in actual and counterfactual scenarios. The actual expected outcomes of adopters is expressed as:

$$E(Y_{jit}|U = j,\ M_{jit},\ \overline{M}_{ji},\ \hat{\lambda}_{jit}) = \beta_j M_{jit} + \vartheta_j \overline{M}_{ji} + \sigma_j \hat{\lambda}_{jit} \tag{7a}$$

[2] Please refer to Khonje et al. (2018) and Kassie et al. (2017) for more detailed explanation.

[3] A falsification test certifies the admissibility of the selection instrument as a valid instrument: if a variable is an appropriate selection instrument, it will only influence the adoption decision, but not the welfare outcomes.

The expected outcomes of adopters had they decided not to adopt (counterfactual)

$$E(Y_{1it}|U=j,\ M_{jit},\ \overline{M}_{ji},\ \hat{\lambda}_{jit}) = \beta_1 M_{jit} + \vartheta_1 \overline{M}_{ji} + \sigma_1 \hat{\lambda}_{jit} \tag{7b}$$

Eq. (7b) represents the outcome for what CSA adopters would have obtained if the coefficients on their characteristics (M_{jit}, $\overline{M}_{ji}$, $\hat{\lambda}_{jit}$) were the same as the coefficients on the characteristics of non-adopters (Khonje et al., 2018; Kassie et al., 2017; Teklewold et al., 2013).

The ATT[4] is computed as the difference between Eq. (7a) and Eq. (7b) (Khonje et al., 2018; Kassie et al., 2017) as follows:

$$\begin{aligned} ATT &= E(Y_{jit}|U=j,\ M_{jit},\ \overline{M}_{ji},\ \hat{\lambda}_{jit}) - E(Y_{1it}|U=j,\ M_{jit},\ \overline{M}_{ji},\ \hat{\lambda}_{jit}) \\ &= M_{jit}(\beta_j - \beta_1) + \hat{\lambda}_{jit}(\sigma_j - \sigma_1) + \overline{M}_{ji}(\vartheta_j - \vartheta_1) \end{aligned} \tag{8}$$

The first term of Eq. (8) ($\beta_j - \beta_1$) captures the expected change in the mean outcome due to the differences in coefficients of the observed characteristics. The second ($\sigma_j - \sigma_1$) and third ($\vartheta_j - \vartheta_1$) terms in Eq. (8) corrects selection bias and endogeneity originating from unobserved heterogeneity (Khonje et al., 2018).

Our indicators for farm level and welfare outcomes are yield (measured as the total output per hectare), intensity of maize commercialization (measured as the ratio of quantity of maize sold to the total output) and own consumption[5] per AEU (measured as the quantity of maize available for consumption divided by adult equivalent unit). The data is limited in terms of exploring other important welfare indicators such as poverty and food security.

3. Data and descriptive statistics

The study was conducted in all the maize growing regions of Ghana except the Greater Accra Region (Fig. 1). The study relied on a panel data (2013 and 2018) which was collected under a joint collaboration between the Consultative Group of International Agricultural Research (CGIAR) (i.e. International Food Policy and Research Institute (IFPRI) and International Institute of Tropical Agriculture (IITA)) and two institutes of Ghana's Council for Scientific and Industrial Research (CSIR) (Crops Research Institute (CRI) and Savanna Agricultural Research Institute (SARI)). The baseline survey was conducted in 2013 by IFPRI, CSIR-CRI, and CSIR-SARI while the endline survey was conducted in 2018 by IITA/CSIR-SARI.

A multi-stage sampling techniques (clustered and randomized sampling procedure) was employed in the selection of the farmers. The sampling framework was all maize-producing districts with more than 3,000 ha (average for 2009–2011) under maize cultivation. In the first stage, the proportional[6] probability sampling approach was used to assign more weight to districts with higher maize productions and followed with random selection of 30 districts. In the second stage, enumeration areas (EAs) were randomly selected in each sampled district. 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). A total of 90 EAs were randomly selected. The third stage was followed by random selection of seven farmers in each of the sampled EAs. In summary, a total of 630 farmers were randomly sampled from 90 EAs in 30 districts of Ghana. Following the definition of Ragasa et al. (2014), a farmer in our sample is defined as one who managed and took decisions about a maize plot during the major season of 2012 (with a minimum of 0.5 acres, or 0.2 ha, of maize area included in the list of maize farmers). A follow up survey of the same households was conducted in 2019 to generate a panel unit for the analysis. We interviewed 555 households (representing 88 % of initial households in 2013) during the endline survey using the same set of questionnaires administered in 2013. Out of the 555 farmers, we observed an attrition effect of 20 % bringing the total sampled units to 438. The attrition effect was mainly due to migration, death, *inter alia*. To achieve a balanced household panel, we dropped households who were not present at the time of the survey.

The data contains information on household demography, farm characteristics, farm management practices, soil improvement technologies, seed source, adoption of DTM varieties, information on extension services related to crop production, risk preferences, and pattern of maize utilization. In this study, we refer to CSA as adoption of DTM varieties and row planting. An adopter is considered to be a farmer who have used the farm technologies for at least a year during the period of the survey. DTM variety and row planting are defined as a dummy variable taking a value of 1 if a farm household uses the technologies. We generated a multinomial choice variable by categorizing households according to their adoption of the two farm technologies in isolation.

Table 1 shows the outcome and explanatory variables (demography, farm, and institutional characteristics of the farm households) used in the analysis. Table A2 in the appendix reports the same outcome and explanatory variables based on adoption of CSA. The average yield, sales intensity, and own consumption per AEU are 1152 kg/ha, 0.69, and 0.64 respectively. By disaggregating the farm and welfare outcomes based on year, we observed that yield and sales intensity are relatively higher in 2013 than in 2018. However, for own consumption per AEU, the value is higher in 2018. The proportion of farm households who adopted DTM variety increased from 59 % in 2013 to 82 % in 2018 while the proportion of households who practice row planting decreased from 75 % in 2013 to 63 % in 2018. The high level of DTM variety adoption may be attributed to the vigorous promotion and technical support provided to farmers by national and international research organizations while high cost of labour may be accounting for the decrease in the use of row planting. Table A2 in the appendix shows that adopters of CSA (IMP_1ROW_0, and IMP_0ROW_1) obtain higher maize yield and sales intensity than non-adopters (IMP_0ROW_0).

Conversely, non-adopters record a higher sales intensity in 2018 than adopters. With the exception of adopters of row planting, adopters of improved maize record higher own consumption per AEU in 2013 but the trend changes in 2018 where all the adopters recorded higher own consumption per AEU than the non-adopters (Table A2). Given that the descriptive statistics are unconditional associations, we are unable to attribute the changes in farm and welfare outcomes to the adoption of CSA since other factors may be driving the changes.

The gender distribution across the sampled households is the same. Sampled households are relatively young, natives with 8 household members and 6 years of formal education. With respect to farm characteristics, 25 %, 18 %, and 53 % of the farmers practice intercropping, are model farmers, and use fertilizer, respectively. About 38 % of the farmers cultivate maize on steep lands. The average farm size and walking distance to the nearest farm plot is 1.68 ha and 45 min, respectively. Farmers travel an average distance of 12 km to the nearest extension office. About 35 %, 39 %, and 53 % of farmers are members of FBOs, have contact with agricultural extension agents, and have been visited by extension agents, respectively.

We further examined the transition and switching behaviour of farm households with respect to the use of CSA during the two periods (Table 2). The study identified four categories of CSA users – “Non-users” (farm household who never used any of the CSA in both periods); “Discontinued users” (farm household who uses a specific CSA in 2013 but not in 2018); “New-users” (farm household who did not use the

[4] The ATT is computed based on the post-estimation prediction of the actual and counterfactual expected value of the outcomes for a household that adopts technology j after estimating the MESR in Eq. (6).

[5] Own consumption is computed by subtracting the amount of maize sold, gifted and seed from the household's own production.

[6] The proportional probability sampling technique assigns districts with a larger production area of maize a higher probability of being selected. The selected districts represent 40 percent of the total maize production area (and 39 percent of the total production in tons or 37 percent of total acreage) in Ghana between 2009 and 2011 (Ragasa et al., 2014).

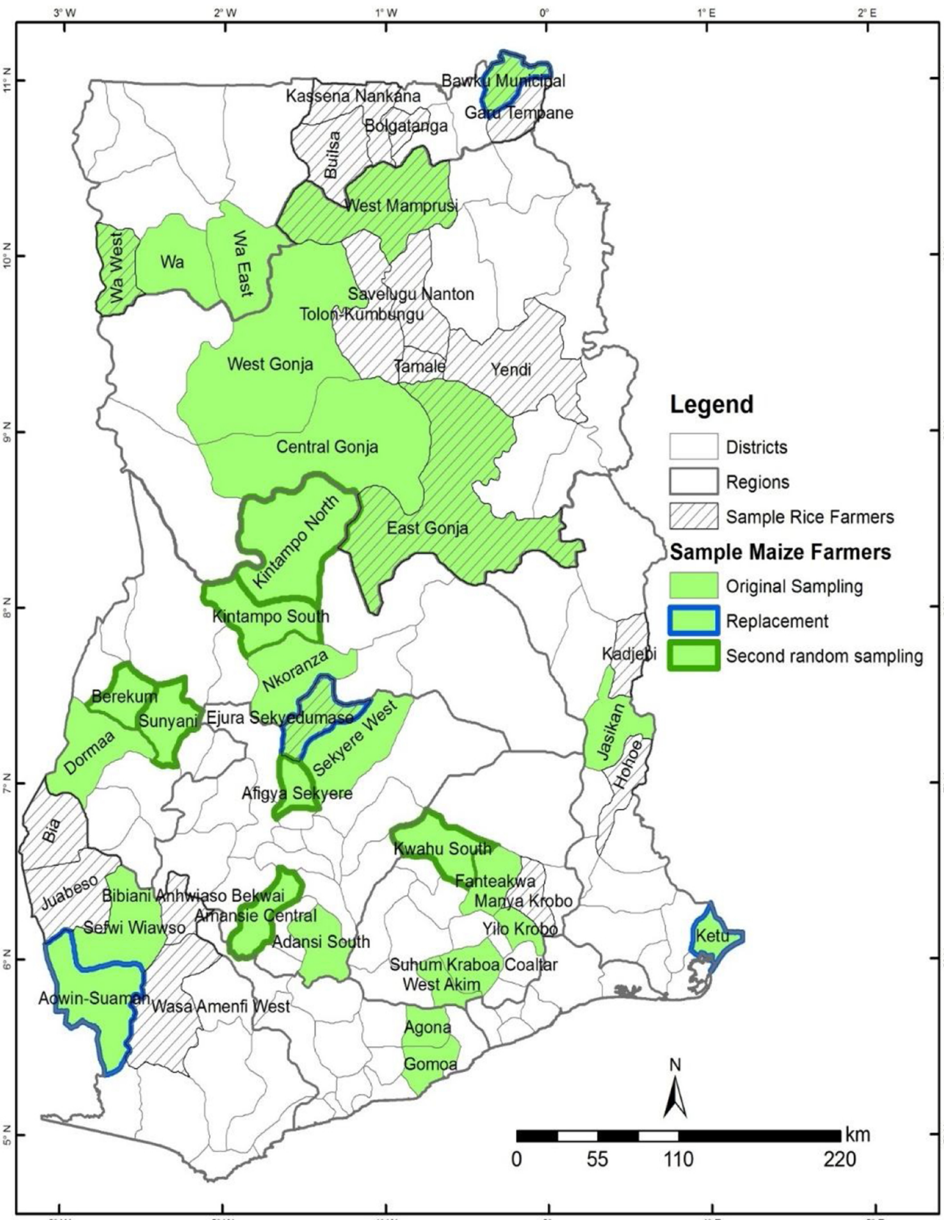

Fig. 1. Sampled districts for the maize and rice adoption study.
Source: Ragasa et al. (2014)

specific CSA in 2013 but adopted in 2018); and "Stayers" (farm households that adopted the same CSA in both periods). The data indicate that 6% and 13 % of the sample households are non-users of improved varieties and row planting, respectively and about 45 % and 36 % of the sampled households switch in and out of improved varieties and row planting, respectively between 2013 and 2018. For stayers, the data shows that 49 % and 51 % used improved varieties and row planting in both periods. Household behaviour regarding dis-adoption and new adoption may be driven by differences in observed and unobserved time-constant and time-varying factors.

4. Results and discussion

4.1. Determinants of adoption of CSA

The marginal effects of the first stage (Eq. 5) MNL regression are presented in Table 3. The results show that factors influencing the choice of CSA differ significantly across technology choices. The Wald test suggests that the explanatory variables included in the MNL selection model provide a good explanation regarding the choice of CSA. The Mundlak and instrumental variables significantly explain the choice of CSA which suggests that failure to account for unobserved heterogeneity and endogeneity will lead to a biased estimate of CSA choice on the outcome variables. Based on the results, the use of pooled MNL selection model is appropriate.

Demographic characteristics such as gender and years of education significantly influence the adoption of DTM variety (IMP_1ROW_0). Female-headed households are 5% more likely to adopt improved varieties compared to male-headed households. Consistent with the findings of Khonje et al. (2018) and Teklewold et al. (2013), educated farmers are more likely to adopt both DTM varieties and row planting. Education is expected to increase farmers' receptivity and utilization of modern technologies. However, the results indicate that education decreases the probability of adopting only improved varieties. The results contradicts the findings of Bezu et al. (2014) who find that education increases the probability and intensity of adopting improved maize

Table 1
Descriptive statistics by survey year.
Source: Authors computation based on IITA-IFPRI panel survey, 2018.

Variables	2013		2018		Pooled sample	
	Mean	SD	Mean	SD	Mean	SD
Outcome variables						
Yield (kg/ha)	1199.10	1082.67	1104.28	1279.59	1152.52	1183.78
Sales intensity	0.74	0.26	0.64	0.31	0.69	0.29
Own consumption per AEU	0.59	0.81	0.69	0.89	0.64	0.85
Treatment variables						
Planted improved varieties (1 = yes)	0.59	0.49	0.82	0.38	0.71	0.46
Practice row planting (1 = yes)	0.75	0.43	0.63	0.48	0.69	0.46
Explanatory variables						
Gender of household head (1 = male)	0.78	0.42	0.23	0.42	0.50	0.50
Age of household head (years)	44.49	11.72	49.21	11.26	46.80	11.73
Education of household head (years)	6.44	5.01	5.54	5.57	5.99	5.31
Nativity (1 = native)	0.63	0.48	0.64	0.48	0.63	0.48
Household size (number)	8.52	5.46	8.40	6.31	8.46	5.90
Practice intercropping (1 = yes)	0.39	0.49	0.09	0.29	0.25	0.43
Distance to plot (minutes)	43.59	36.64	46.97	40.02	45.25	38.36
Owns land (1 = yes)	3.41	1.89	3.27	1.18	3.34	1.60
Farm size (hectare)	1.56	1.54	1.80	2.24	1.68	1.92
Slope (1 = slope)	0.44	0.50	0.32	0.47	0.38	0.49
Model farmer (1 = yes)	0.27	0.44	0.10	0.30	0.18	0.39
Use fertilizer (1 = yes)	0.50	0.50	0.57	0.50	0.53	0.50
Fertilizer use (years)	3.30	3.69	6.67	4.24	4.52	4.21
Owns bicycle (1 = yes)	0.52	0.50	0.94	0.23	0.73	0.44
Owns motor (1 = yes)	0.19	0.40	0.95	0.23	0.57	0.50
Owns sprayer (1 = yes)	0.65	0.48	0.93	0.25	0.79	0.41
Instrumental variables						
Distance to extension (kilometers)	11.61	29.52	12.94	56.82	12.27	45.19
Member of FBO (1 = yes)	0.29	0.46	0.41	0.49	0.35	0.48
Household head contact extension (1 = yes)	0.28	0.45	0.49	0.50	0.39	0.49
Extension contact household head (1 = yes)	0.50	0.50	0.55	0.50	0.53	0.50

Notes: SD refers to standard deviations.

Table 2
Transitions in CSA practices (%) over the sample periods (2013 and 2018).

Good Agricultural Practices	Non-users	Discontinued	New-users	Stayers
Improved varieties	6.39	11.19	33.79	48.63
Row planting	12.79	24.43	11.64	51.14

varieties in Malawi. Educated household heads are likely to engage in off-farm activities that guarantees relatively high and reliable income thus reducing their effort in agricultural activities. In Ghana (especially the northern part—Upper East, Upper West and Northern regions), most of the DTM seeds were distributed to farmers through a development project, and therefore, farmers are in these regions are less likely to buy improved seed. Household size increases the adoption of row planting (IMP_0ROW_1) but decreases the adoption of DTM varieties. Row planting is labour-intensive thus the positive correlation with household size. The results is consistent with Fentie and Beyene (2019) who find a positive relationship between household size and row planting in Ethiopia. Nativity (form of social capital) increases the probability of using improved maize seed. Natives usually have access to communal resource such as land for agricultural activities and more likely to benefit from agricultural development programs.

Distance to farm plots decreases the adoption of row planting. Modern technologies are more likely to be adopted on farm plots closer to the households. Fertilizer use is negatively associated with the adoption of only DTM varieties. The finding could be due to the complementarity or substitutability between fertilizer and CSA. In addition, cost of fertilizer may be driving the low adoption of DTM seed given a farmer needs to apply fertilizer to DTM seed in order to get optimum yield. There is the need to encourage farmers to complement DTM variety with fertilizer. The results further show that adoption of row planting is positively related with slope of farm plot. Ownership of motor bicycle increases the adoption of DTM (11 %) but decreases the probability of adopting only row planting (23 %). Khonje et al. (2018) found a similar result where assets increase the adoption of improved maize and conservation practices in Zambia. Farmers who own assets can liquidate it when exposed to extreme negative weather and income shocks and invest in modern inputs and CSA practices. The probability of only adopting row planting is higher for farmers who have contact with agricultural extension agents. Consistent with our findings, Fentie and Beyene (2019) find a positive relationship between extension and row planting in Ethiopia. Surprisingly, we find no significant effects of farm size and land ownership on the adoption of CSA despite their importance based in the literature (Khonje et al., 2018; Wainaina et al., 2016; Bezu et al., 2014; Kamau et al., 2014).

4.2. Impacts of CSA on farm and welfare outcomes

Table 4 highlights the impact of CSA on yield, sales intensity, and own consumption per AEU under actual and counterfactual conditions after controlling for selection bias. The results from the second stage regression show that some of the time averages and selection correction terms are significant in most of the outcome equations. Table A3 in the appendix presents the results of the unconditional average effects (an indication of the effect of CSA on outcomes) of adoption on yield, intensity of commercialization, and own consumption per AEU derived from the actual and counterfactual distributions. On the average, adopters of CSA recorded higher maize yield and intensity of commercialization than non-adopters. Conversely, non-adopters of CSA realized higher own consumption per AEU than adopters. These results do not account for selection bias due to both observed and unobserved factors. However, the results in Table 4 accounts for selectivity bias.

The results show that adoption of CSA impacts positively on maize yield. The adoption of row planting (IMP_0ROW_1) recorded the highest

Table 3
Marginal effect of adoption of agricultural technologies.
Source: Authors estimation based on IITA-IFPRI panel survey, 2018.

Variables	(IMP_1ROW_0) Marginal effect	Robust Std. error	(IMP_0ROW_1) Marginal effect	Robust Std. error
Gender (1 = male)	−0.053*	0.028	−0.032	0.029
Age (log)	0.052	0.122	0.020	0.132
Years of education (log)	−0.030**	0.012	−0.009	0.012
Household size (log)	−0.070*	0.039	0.094*	0.049
Distance to farm plot (log)	−0.014	0.018	−0.038*	0.019
Fertilizer use (years)	−0.105***	0.025	−0.019	0.024
Plot size (log)	0.044	0.044	0.006	0.047
Land ownership (1 = yes)	−0.001	0.013	0.020	0.015
Nativity (1 = native)	0.048*	0.028	−0.028	0.028
Slope of farmland (1 = slope)	−0.017	0.054	0.098*	0.056
Model farmer (1 = yes)	−0.061	0.040	−0.050	0.035
Practice intercropping (1 = yes)	0.034	0.054	0.062	0.060
Owns motor (1 = yes)	0.110**	0.045	−0.227***	0.048
Extension contact farmer	−0.003	0.045	0.083***	0.050
Farmer contact extension	−0.055	0.050	−0.018	0.049
Distance to extension (log)	0.012	0.017	0.018	0.016
Mundlak variables	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Joint significance of instrumental variables χ^2 (3)	6.65*			
Joint significance of time-varying covariates: χ^2 (36)	69.41***			
Wald χ^2 (60)	157.14***			

Notes: The reference category is non-adoption (IMP_0ROW_0). IMP_1ROW_0— only DTM variety; IMP_0ROW_1— only row planting. The Mundlak device was incorporated in the estimation but the variables (mean of the time-varying explanatory variables) are not presented in the interest of brevity.

positive yield effect (271 kg/ha) followed by the adoption of DTM varieties (IMP_1ROW_0) which increases maize yield by 122 kg/ha. In eastern Zambia, Khonje et al. (2015) find a positive effect of improved maize varieties on yield. Alemu et al. (2014) observe that row planting increases yield by 14 % in Ethiopia. Contrary to our findings, Vandercasteelen et al. (2018) did not find any significant effect of row planting on teff yield in Ethiopia.

With respect to the intensity of commercialization, the results show that on the average adopters of CSA are more likely sell a larger share of their maize. The results indicate that both DTM seed and row planting have differential effects on the intensity of maize commercialization. For example, while adopters of row planting (IMP_0ROW_1) recorded relatively higher positive intensity of maize commercialization of 0.13, adopters of DTM varieties (IMP_1ROW_0) realized the lowest intensity of maize commercialization (0.09). We expect higher maize yield to translate to higher market participation assuming market conditions are favourable to smallholder farmers. Farm households participate in output markets to generate income in order to meet household expenditures. In addition, they participate in market to diversify their food choices by exchanging own production with other food items not produced within the households. The results suggest that by encouraging the use of CSA, there is the likelihood of increasing market participation that will translate to higher income and increase food choices within farm households.

The results reveal that adoption of CSA reduces own consumption per AEU. Adoption of only improved maize varieties have a negligible negative effect on own consumption per AEU while adoption of row planting (IMP_0ROW_1) have a negative effect on own consumption per AEU. These results are expected given that adoption of CSA increases household maize commercialization intensity thus the quantity of own consumption would also be expected to decline. It is possible that reduction in own consumption may be complemented with increase in consumption of other food items not directly produced by the households. Household food diversification may be driving the negative effect of CSA on own consumption. Our results contradict 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.

4.3. Alternative specifications: IV-fixed effects

To check for robustness of our results, we use an alternative specification (IV fixed effects panel regression) that account for the endogeneity in the choice of CSA. The results of this estimation are reported in Table 5. The estimation is consistent with the previous findings where adoption of CSA impacts positively on maize yield and intensity of maize commercialization but impact negatively on own consumption per AEU. However, the magnitudes of the effects of adoption on maize yield and own consumption per AEU is consistently lower for the MESR-based estimates (Table 4) compared to the IV-fixed effects (Table 5). With the exception of adopters of only DTM varieties, the magnitudes of the MESR-based estimates is consistently higher for row planting relative to the IV-fixed effects estimates. Despite the differences in the scale of effect, our results show that adoption of CSA influences farm and welfare outcomes

5. Conclusion

Most studies in SSA have focused on the adoption of single agricultural technologies on the welfare of smallholder farmers. Yet little is known about the impact of row planting on farm and welfare outcomes despite vigorous promotion of CSA practices by development organizations. This paper examines the adoption and farm and welfare

Table 4
Impact of CSA on yield and food security.
Source: Authors computation based on IITA-IFPRI panel survey, 2018.

Outcome variables	Technology choice	Adoption status: Adopters	Adoption status: Non-adopters	Average treatment effect on treated
Maize yield (kg/ha)	IMP_1ROW_0	927.14 (55.26)	804.74 (95.13)	122.40* (91.82)
	IMP_0ROW_1	1098.16 (36.71)	827.66 (57.39)	270.50*** (66.39)
Sales intensity	IMP_1ROW_0	1.62 (0.02)	1.54 (0.03)	0.09***(0.03)
	IMP_0ROW_1	1.68 (0.02)	1.55 (0.02)	0.13*** (0.02)
Own consumption per AEU	IMP_1ROW_0	1.57 (0.04)	1.57 (0.02)	−0.00 (0.04)
	IMP_0ROW_1	1.56 (0.03)	1.67 (0.03)	−0.11*** (0.03)

Notes: The reference category is non-adoption (IMP_0ROW_0); IMP_1ROW_0— adoption of only DTM maize varieties; IMP_0ROW_1— only row planting; AEU refers to adult equivalent unit. The values in parentheses are standard errors. The mean values of yield, intensity of commercialization, and own consumption for the non-adoption category are 1094.78 kg/ha, 0.68, and 0.58 respectively.

Table 5
Robustness checks on welfare effects of adopting CSA.

	Instrumental Variable Fixed Effects		
Choices of CSA	Maize yield	Sales intensity	Own consumption
IMP_1ROW_0	403.34**	0.19***	−0.73**
	(176.65)	(0.03)	(0.36)
IMP_0ROW_1	342.14***	0.04***	−0.95*
	(3.05)	(0.01)	(0.57)

Note: Robust standard errors are in parentheses. The mean values of yield, intensity of commercialization, and own consumption for the non-adoption category are 1094.78 kg/ha, 0.68, and 0.58 respectively.

impacts of CSA using a recent panel data from Ghana. We employ a multinomial endogenous switching regression model to correct for endogeneity and selection bias in the choice of CSA.

Our results suggest that adoption of DTM varieties is generally high over the period of study but the adoption of row planting decreased for the same period. In promoting CSA among smallholder farmers, key factors to consider include gender, years of formal education, distance to farm plots, fertilizer use, inter-cropping, assets ownership, and access to extension services. Our results further showed that adoption of CSA increases maize yields and intensity of maize commercialization but decreases own consumption per AEU. In terms of heterogeneity effect, we find evidence of higher effect of adoption of row planting on maize yield, commercialization intensity and own consumption per AEU relative to the adoption of only DTM varieties. However, the study is limited in identifying whether a decrease in own consumption increases consumption of food away from home and non-food expenditures.

Our results provide valuable information about the choice of CSA that can benefit smallholder farmers taking into consideration the resource constraints they face. However, these gains may be consolidated when the gender inequality gap in terms of access to technology is addressed coupled with increasing the visibility of agricultural technologies through extension agents. From policy perspective, farmers must be encouraged to use row planting as a strategy to increase agricultural performance and welfare outcomes. This can be achieved by using extension agents to create awareness coupled with farmer trainings programs. Furthermore, adoption of CSA have the tendency to increase household food diversification due to the decrease in own consumption per AEU.

Although this study is informative, lack of data on other CSA and the short panel of the data-set limits detail analysis of the variation in the use of CSA. We are unable to conduct a benefit cost analysis that will inform policy-makers on which of the choices of CSA is more economically rewarding and cost-effective. Second, the study will benefit much from using the area under each of the practices as intensity measurement relative to count measurement. Third, establishing the relationship between adoption of CSA and own consumption and food purchases to supplement household nutrition requirement is key. These remain for the future.

Declaration of Competing Interest

The authors declare that this manuscript is original and there is no conflict of interest

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Appendix A

Table A1
Test of the validity of the instrument (falsification test).

Panel A	Maize yield†		
	IMP_0ROW_0 (1)	IMP_1ROW_0 (2)	IMP_0ROW_1 (3)
Extension contact farmer	−0.087 (0.173)	0.079 (0.095)	−0.052 (0.187)
Farmer contact extension	−0.196 (0.196)	0.055 (0.096)	0.104 (0.174)
Distance to extension (log)	–	−0.002 (0.002)	0.002 (0.001)
F-values	F(2, 101) = 0.75	F(3, 339) = 0.79	F(3, 70) = 0.67
	Sales intensity†		
Panel B	IMP_0ROW_0	IMP_1ROW_0	IMP_0ROW_1
	(1)	(2)	(3)
Extension contact farmer	0.034 (0.034)	−0.021 (0.019)	−0.049 (0.042)
Farmer contact extension	0.006 (0.037)	0.022 (0.019)	−0.009 (0.039)
Distance to extension (log)	−0.001 (0.002)	−0.000 (0.00)	0.000 (0.000)
F-values	F(3, 113) = 0.49	F(3, 340) = 0.70	F(3, 70) = 1.16
	Own consumption†		
Panel C	IMP_0ROW_0	IMP_1ROW_0	IMP_0ROW_1
	(1)	(2)	(3)
Extension contact farmer	0.072 (0.052)	0.014 (0.038)	0.111 (0.083)
Farmer contact extension	–	0.014 (0.038)	0.003 (0.078)
Distance to extension (log)	–	–	−0.001 (0.001)
F-values	F(1, 115) = 1.93	F(2, 341) = 0.18	F(3, 70) = 1.25

Notes: IMP_0ROW_0 is the reference category. † indicate variables expressed in natural logarithm. Standard errors are in parentheses.

Table A2
Descriptive statistics by survey year and adoption status.
Source: Authors estimation based on IITA-IFPRI panel survey, 2018.

Variable	2013						2018					
	IMP_0ROWo		IMP_1ROW_0		IMP_0ROW_1		IMP_0ROWo		IMP_1ROW_0		IMP_0ROW_1	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD.
Yield	1144	1077	1200	983	1332	1028	961	552	1160	1690	1301	1169
Sales intensity	0.67	0.32	0.77	0.24	0.75	0.25	0.70	0.36	0.61	0.32	0.54	0.31
Own consumption	0.55	0.67	0.63	0.68	0.47	0.44	0.64	0.84	0.70	0.95	1.03	1.05
Age	45.2	13.6	44.4	11.8	44.6	11.9	48.0	12.0	50.8	10.9	47.5	11.5
Education (years)	4.7	4.9	5.4	4.8	6.2	5.0	3.1	4.9	4.2	5.4	4.8	5.9
Nativity	0.7	0.5	0.6	0.5	0.6	0.5	0.4	0.5	0.6	0.5	0.7	0.5
Household size	9.7	6.2	9.0	7.1	8.7	6.2	6.0	6.9	9.1	8.9	10.0	4.2
Intercropping	0.6	0.5	0.6	0.5	0.4	0.5	0.1	0.2	0.1	0.3	0.0	0.2
Plot distance	43.2	40.3	47.4	38.3	37.6	33.3	28.4	35.7	43.6	35.3	33.9	40.4
Owns land	3.3	2.0	3.3	1.7	3.5	1.8	1.7	1.8	3.1	1.4	3.0	1.6
Plot size	1.6	1.3	1.9	2.2	1.6	1.8	1.4	1.0	1.9	2.3	1.7	1.9
Land slope	0.4	0.5	0.4	0.5	0.4	0.5	0.6	0.5	0.3	0.4	0.4	0.5
Used fertilizer	0.2	0.4	0.3	0.5	0.5	0.5	0.4	0.5	0.4	0.5	0.8	0.4
Model farmer	0.3	0.4	0.2	0.4	0.2	0.4	0.0	0.0	0.1	0.2	0.1	0.3
Fertilizer use (years)	1.5	3.1	2.0	3.6	3.1	3.4	2.7	4.1	2.6	4.2	6.6	6.5
Owns bicycle	0.4	0.5	0.5	0.5	0.5	0.5	0.7	0.4	1.0	0.2	1.0	0.2
Owns motor	0.2	0.4	0.2	0.4	0.2	0.4	0.7	0.4	1.0	0.2	1.0	0.2
Owns sprayer	0.5	0.5	0.6	0.5	0.7	0.5	0.7	0.4	0.9	0.3	1.0	0.2
Distance to extension	19.5	68.8	8.0	8.2	10.3	12.0	5.1	7.6	8.9	13.7	7.0	6.2
Member of FBO	0.2	0.4	0.3	0.5	0.2	0.4	0.4	0.5	0.3	0.5	0.5	0.5
Contact extension	0.1	0.3	0.2	0.4	0.3	0.4	0.5	0.5	0.3	0.5	0.7	0.5
Extension contact	0.3	0.5	0.5	0.5	0.5	0.5	0.6	0.5	0.4	0.5	0.8	0.4

Notes: The reference category is non-adoption (IMP_0ROWo). IMP_1ROW_0— only improved maize varieties; IMP_0ROW_1—only row planting; SD refers to standard deviations.

Table A3
Unconditional average effects of adoption of CSA on yield and food security.
Source: Authors computation based on IITA-IFPRI panel survey, 2018.

Outcome variables	Technology choice	Adoption status		Unconditional average effect
		Adopters	Non-adopters	
Maize yield (kg/ha)	IMP_1ROW_0	1115.67 (31.67)	871.44 (29.62)	244.23*** (36.63)
	IMP_0ROW_1	1109.63 (18.96)	871.44 (29.62)	238.19*** (31.63)
Sales intensity	IMP_1ROW_0	1.68 (0.01)	1.58 (0.01)	0.10***(0.01)
	IMP_0ROW_1	1.68 (0.01)	1.58 (0.01)	0.10*** (0.01)
Own consumption per AEU	IMP_1ROW_0	1.68 (0.02)	1.62 (0.01)	0.06 (0.11)
	IMP_0ROW_1	1.57 (0.03)	1.62 (0.01)	−0.05** (0.02)

Notes: The reference category is non-adoption (IMP_0ROW_0); IMP_1ROW_0— only DTM varieties; IMP_0ROW_1— only row planting. AEU refers to adult equivalent unit. The mean values of yield, intensity of commercialization, and own consumption for the non-adoption category are 1094.78 kg/ha, 0.68, and 0.58 respectively.

Appendix B. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.landusepol.2020.104622.

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