Routledge
Taylor & Francis Group

Agrekon

Agricultural Economics Research, Policy and Practice in Southern Africa

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/ragr20

Does the use of multiple agricultural technologies affect household welfare? Evidence from Northern Ghana

Wencong Lu, Kwabena Nyarko Addai & John N. Ng'ombe

To cite this article: Wencong Lu, Kwabena Nyarko Addai & John N. Ng'ombe (2021) Does the use of multiple agricultural technologies affect household welfare? Evidence from Northern Ghana, Agrekon, 60:4, 370-387, DOI: 10.1080/03031853.2021.1992290

To link to this article: https://doi.org/10.1080/03031853.2021.1992290

Published online: 02 Nov 2021.

AGREKON
2021, VOL. 60, NO. 4, 370–387
https://doi.org/10.1080/03031853.2021.1992290

Does the use of multiple agricultural technologies affect household welfare? Evidence from Northern Ghana

Wencong Lu[a], Kwabena Nyarko Addai [a] and John N. Ng'ombe [b]

[a]Department of Agricultural Economics and Management, Zhejiang University, Hangzhou, People's Republic of China; [b]Department of Agribusiness, Applied Economics and Agriscience Education, North Carolina Agricultural and Technical State University, Greensboro, NC, USA

ABSTRACT
Agricultural intensification has been encouraged through the promotion of various agricultural technologies, but the synergies between different technologies have not been fully explored among various specific crops. Using the multinomial endogenous switching regression model complemented with the multivalued inverse probability regression model, this study determines the impacts of the adoption of combinations of chemical fertiliser, improved rice seeds, and herbicides on household welfare. Data were collected from 900 farm households in Northern Ghana. Our results indicate that the adoption of combinations of agricultural technologies is affected by various socio-economic attributes, resource constraints, institutional factors, and production shocks. We find that adopting multiple technologies improves rice yields, gross rice income, and per capita consumption expenditure. The results point out the crucial synergistic effects of the adoption of agricultural technologies on household welfare. We suggest that policies aimed at strengthening farm household welfare should encourage adopting multiple agricultural technologies in rice-producing farm households to realise the most welfare.

ARTICLE HISTORY
Received 3 September 2020
Accepted 4 October 2021

KEYWORDS
Agricultural technologies; per capita consumption expenditure; endogenous switching regression; rice yield

1. Introduction

African countries are faced with numerous developmental challenges that have culminated in significantly low living standards (Barrios, Bertinelli, and Strobl 2010). Notwithstanding, the continent has made meaningful strides macro-economically over the years, resulting in stable economic growth (Rodrik 2018). Since 2000, Africa's Gross Domestic Product (GDP) has increased at an average yearly rate of 5.2%. Additionally, as of 2017, six out of the 13 fastest-growing economies in the world were in Africa. Although there has been some improvement in economic performance, poverty and food insecurity in sub-Saharan Africa (SSA) remain high. About two out of three of SSA's population resides in rural areas, most of which depend on agriculture for their livelihood (Diao, Hazell, and Thurlow 2010). These gains in macroeconomic performance in the continent have hardly been felt in the agricultural sector and rural areas. The agricultural sector in SSA continues to underperform. Continental crop yields lag behind other world regions, while productivity growth continues to be sluggish (Julien, Bravo-Ureta, and Rada 2019; Sheahan and Barrett 2017). Between 1961 and 2000, average cereal yields have fluctuated around 0.8 ton/ha and only experienced a modest increase afterward to reach 1.3 ton/ha in 2014 (Fao 2018). The low crop yields and high levels of food insecurity can be explained by low adoption of new agricultural technologies,

CONTACT Kwabena Nyarko Addai knaddai@gmail.com Department of Agricultural Economics and Management, Zhejiang University, 310058 Hangzhou, People's Republic of China

climate change, pests and diseases, and low soil fertility (Kassie et al. 2015; Khonje et al. 2018). However, to mitigate these challenges, most farmers in SSA have resorted to crop diversification which helps to improve their resilience (Mzyece and Ng'ombe 2020).

As part of crop diversification and consumption patterns, rice has unsurprisingly become the second staple food consumed in Ghana after maize (Lu, Addai, and Ng'ombe 2021). For example, rice production in Ghana increased from 48,800 tons in 1970–925,000 tons in 2019, growing at an average annual rate of 9.03% (Taylor 2020). Despite high rice consumption levels and the crop's potential to boost the country's economic prospects, rice remains a food crop that Ghana is not self-sufficient in, with consumption exceeding domestic production (Lu, Addai, and Ng'ombe 2021). Thus, increasing rice yields through the increased adoption of improved technologies is critical to reducing food insecurity and poverty. However, the debate about which type of technology is more appropriate to foster sustainable development among smallholder farmers still remains. While others consider low-external input strategies as most appropriate (Altieri and Toledo 2011), others suggest input intensification (Borlaug 2007; Pingali 2014). On one hand, low-external input strategies involve different agronomic practices such as conservation tillage, other soil and water management techniques, and organic manure (Wainaina, Tongruksawattana, and Qaim 2018). On the other hand, the input intensification approach emphasises the use of improved seeds, chemical fertiliser, irrigation, and other productivity-enhancing external inputs. Proponents of the low-external inputs approach often argue that the use of improved crop varieties and agrochemicals would negatively impact the environment and create farmer dependencies with negative implications on food security (Holt-Giménez et al. 2012). The other side of the debate has it that the use of improved seeds and increased chemical fertiliser is essential for boosting food security, especially in SSA, where the Green Revolution did not take off at the same level as other world regions (Jhamtani 2011; Juma 2013). As an alternative to the search for an all-purpose system, Kassie et al. (2018) and Wainaina, Tongruksawattana, and Qaim (2016) suggest that appropriate approaches may vary from one country to another, contingent on agro-ecological zones, different crops, social, economic, and market settings.

Moreover, recent studies suggest that farmers sometimes adopt a combination of these technologies (Danso-Abbeam and Baiyegunhi 2018; Kassie et al. 2015). Wainaina, Tongruksawattana, and Qaim (2018) indicated that a synergistic relationship among agricultural technologies could positively impact productivity and incomes. While this is possible, there is little evidence about crop-specific synergetic relationships of agricultural technologies in diverse smallholder environments, especially in SSA. This is primarily as a result of the fact that most impact studies focus on single technologies (Becerril and Abdulai 2010; Khonje et al. 2015; Lu, Addai, and Ng'ombe 2021) or compare the effect of similar types of technologies (Biru, Zeller, and Loos 2019; Teklewold et al. 2013; Wainaina, Tongruksawattana, and Qaim 2018).

Few such studies (e.g., Danso-Abbeam and Baiyegunhi 2018; Khonje et al. 2018; Teklewold et al. 2013) widened their scope to include the impact of selected agricultural technologies in combinations, and more so, most of these analyse their effects mostly on maize production. As an emerging relevant body of literature, more evidence in different crops and settings is needed to guide future agricultural technology approaches, especially in SSA. Therefore, this study examines the adoption of multiple agricultural technologies (chemical fertiliser, improved rice seeds, and herbicides) and their effect on farm household welfare (rice yield, gross rice income per hectare, and per capita consumption expenditure). Specifically, we evaluate the determinants of the adoption of these combinations of agricultural technologies in rice-producing farm households and determine the impacts of selected combinations on the outcome variables. Most studies (e.g., Becerril and Abdulai 2010; Khonje et al. 2015; Lu, Addai, and Ng'ombe 2021) do not unearth the full account of combinations of agricultural technologies in rice production, and this study fills this gap.

This study contributes the following to the literature. We examine whether agricultural technology adoption in combinations yields more benefits to the rice-producing farm household than adopting them in singles. This is relevant to the research as to whether farmers should apply agricultural technologies individually or as a combination which would be important for effective extension policies directed at agricultural technology use in SSA. Wu and Babcock (2006) suggested that impact analysis of technologies that ignore the synergies between them may underestimate the impact of the various determinants of adoption decisions and the effects of multiple technology adoption. To the best of our knowledge, this study is the first to take such an approach to analyse the impacts of adopting these unique agricultural technologies (i.e., chemical fertiliser, improved rice seeds, and herbicides) on household welfare in Northern Ghana.

The rest of the paper proceeds as follows. Section 2 presents the econometric framework and strategies for the estimations. Section 3 outlines the data employed in the study and its description. The empirical results and discussions are presented in Section 4. The final section concludes the study.

2. Econometric framework and estimation strategy

Considering the potential agronomic effects among agricultural technologies, farmers that act "efficiently" are likely to adopt agricultural technologies complementarily (Gebremariam and Tesfaye 2018; Wainaina, Tongruksawattana, and Qaim 2018). Conventionally, agricultural technologies (i.e., input and farm practices) may be adopted in combination due to their complementary effects. The reason may be that agricultural inputs are frequently provided to farmers in conjunction with others or handed over collectively through state support programs (Sheahan and Barrett 2017). In practice, some studies on agricultural technology adoption choices (e.g., Danso-Abbeam and Baiyegunhi 2018; Wossen et al. 2019a) assume that farmers consider an array (or package) of possible technologies and select specific technology packages that maximise expected utility. To untie the real effects of multiple technology adoption, we model farmer's choice of combinations of agricultural technologies and their impact using a multinomial endogenous switching regression framework – a selection bias correction approach built on the multinomial logit choice model (Bourguignon, Fournier, and Gurgand 2007). A multinomial endogenous switching regression model generates consistent estimates of the choice procedure regardless of whether the independence of irrelevant alternatives (IIA) assumption is satisfied or not (Bourguignon, Fournier, and Gurgand 2007). This method can determine the impacts of agricultural technology usage in singles and combinations while accounting for potential selection bias from observed and unobserved confounders and the synergy among alternative choices of agricultural technologies (Mansur, Mendelsohn, and Morrison 2008).

2.1 Multinomial adoption selection model

Conceptually, the choice of combinations of agricultural technologies is modelled within a random utility framework. Following Danso-Abbeam and Baiyegunhi (2018), Ng'ombe, Kalinda, and Tembo (2017) and Teklewold et al. (2013), we hypothesise that rice producers seek to maximise their returns U_i, by comparing benefits derived by m alternative combinations of agricultural technologies. A prerequisite for the rice producer i to select any combination, j over an alternative mix m, is when $U_{ij} > U_{im} m \neq j$, or equivalent $\Delta U_{im} = U_{ij} - U_{im} > 0 \; m \neq j$. The probable return, U^*_{ij}, that the rice producer obtains from the selection of the combination j is an inherent factor arrived at through identified household, farm, location-specific characteristics (X_i), and invisible factors (ε_{ij}):

$$U^*_{ij} = X_i\beta_j + \varepsilon_{ij}, \tag{1}$$

where X_i denotes observed exogenous factors (household, farm, and location-specific characteristics), β_j denotes unknown parameters, and ε_{ij} is a random error. Let I be an indicator that designates rice producers' selection of the combination corresponding to:

$$I = \begin{cases} 1 \; if \; U^*_{i1} > \max\limits_{m \neq j} (U^*_{im}) \text{ or } \eta_{i1} < 0 \\ \vdots \quad \vdots \quad \quad \vdots \quad for \text{ all } m \neq j \\ j \; if \; U^*_{i1} > \max\limits_{m \neq j} (U^*_{im}) \text{ or } \eta_{ij} < 0 \end{cases} \tag{2}$$

where $\eta_{ij} = \max_{m \neq j} (U^*_{im} - U^*_{ij}) < 0$ (Bourguignon, Fournier, and Gurgand 2007). Equation (2) suggests that the ith rice producer will select a combination j expecting maximum benefit if combination j leads to higher expected economic benefits than any other combination $m \neq j$, that is, if $\eta_{ij} = \max_{m \neq j} (U^*_{im} - U^*_{ij}) > 0$.

Assuming that ε is identically and independently Gumbel distributed, the likelihood that a rice producer i will select combination j can be modelled using the multinomial logit model (McFadden 1973) as follows:

$$P_{ij} = \Pr(\eta_{ij} < 0 \mid X_i) = \frac{\exp(X_i \beta_j)}{\sum\limits_{m=1}^{j} \exp(X_i \beta_m)} \tag{3}$$

where parameters and variables are as defined before.

2.2 Multinomial endogenous switching regression

The second step of the multinomial endogenous switching regression model involves modelling the relationship between the outcome variables (hereafter, rice yield, gross rice income, and per capita consumption expenditure) and a set of exogenous factors (household, farm, and location-specific factors) for the selected combinations. In our agricultural technology combinations (Table 2), the base category is non-adoption of agricultural technologies (i.e., $C_0I_0H_0$), which is designated as $j = 1$ with the rest portfolios being designated as 2,3, … , n. The outcome model for each likely regime j is specified as:

$$\begin{cases} \text{Regime } 1{:}Q_{i1} = Z_i \alpha_1 + u_{i1} \text{ if } I = 1 \\ \quad \vdots \quad \quad \quad \vdots \\ \text{Regime } 1{:}Q_{ij} = Z_i \alpha_j + u_{ij} \text{ if } I = 1 \end{cases} \tag{4}$$

where $Q'_{i1}s$ are the outcome variables of the ith rice producer in the regime j and error term ($u's$) whose $E(u_{ij}|X, Z) = 0$ and $\text{var}(u_{ij}|X, Z) = \sigma^2_j$. It is assumed that Q_{ij} is identified if, and only if, the combination j is adopted, which happens when $U^*_{ij} > \max\limits_{m \neq j} (U^*_{im})$. If the ε's and u's are not independent, OLS estimations for Equation (4) will be biased. Consistent maximum likelihood estimates of α_j necessitate the addition of the selection correction terms of the selection in Equation (4). The Dubin and McFadden (1984) model assumes the following linearity hypothesis: $E(u_{ij}|\varepsilon_{i1 \ldots\ldots} \varepsilon_{ij}) = \sigma_j \sum\limits_{m \neq j}^{j} r_j(\varepsilon_{im} - E(\varepsilon_{im}))$, whereby $\sum\limits^{j} m = 1^{r_j = 0}$(by construction, the correlation between u's and ε's sums to zero). Under this assumption, the multinomial endogenous switching regression model in Equation (4) can be rewritten as:

$$\begin{cases} \text{Regime } 1{:}Q_{i1} = Z_i \alpha_1 + \sigma_1 \hat{\lambda}_1 \, \omega_{i1} \text{ if } I = 1 \\ \quad \vdots \quad \quad \quad \vdots \\ \text{Regime } 1{:}Q_{ij} = Z_i \alpha_j + \sigma_j \hat{\lambda}_j \, \omega_{ij} \text{ if } I = 1 \end{cases} \tag{5}$$

where σ_j is the covariance between ε's and u's, λ_j is the inverse Mills ratio computed from the estimated probabilities in Equation (3) as $\lambda_j = \sum_{m \neq j}^{j} \rho_j \left[\frac{\widehat{P}_{im} \ln(\widehat{P}_{im})}{1 - \widehat{P}_{im}} + \ln(\widehat{P}_{ij}) \right]$, where ρ, is the correlation coefficient of ε's and u's, and ω's are error terms with a possible value of zero. The standard errors estimated in Equation (5) were bootstrapped using 100 replications to account for potential heteroskedasticity resulting from the derived regressor (λ_j).

According to Lokshin and Glinskaya (2009), the systems of Equations (3) and (5) are identified by nonlinearities even if vectors of observables X and Z overlap completely. Besides, the all-encompassing nature of our data helps in minimising the identification problem. Instrumental variables have been proposed in the literature to provide robust estimates, even though finding a suitable one is non-trivial. However, Chamberlain and Griliches (1975) posited that a system of equations does not necessarily require instrumental variables for identification. Notwithstanding, various authors (e.g., Bourguignon, Fournier, and Gurgand 2007; Danso-Abbeam and Baiyegunhi 2018; Teklewold et al. 2013) have suggested the relevance of instrumental variables in the alternative selection model in Equation (4). Therefore, in addition to selecting the instruments automatically generated by the nonlinearity of the selection model, for model identification, we used the variables extension access and market information as instruments, following literature to identify the selection equation. These variables are plausible because they affect the adoption of the technologies considered here but do not affect outcome variables. Most importantly, in checking their validity, we conducted an admissibility test (Di Falco, Veronesi, and Yesuf 2011) to confirm that these variables jointly ($\chi^2 = 70.07$, $p = 0.000$) affect the adoption of agricultural technologies but not the outcomes.

2.3 Estimation of the counterfactual and treatment effects

Following Danso-Abbeam and Baiyegunhi (2018) and Di Falco and Veronesi (2014), we define how the multinomial endogenous switching regression model can be utilised to compute the counterfactual and average selection impacts. The counterfactual is specified as the outcome variable of adopters that would have been obtained if benefits (coefficients) on their attributes had remained similar to the benefits (marginal effects) on the attributes of the non-adopters and vice versa. That is, the average treatment effect (ATE) is compared to the likely effects on adopters with and without adoption. In addition to tackling selection bias due to unobserved heterogeneity, this procedure likewise reduces selection bias from observed heterogeneity. From Equation (5), the resulting conditional expectations for each outcome variable can be specified as follows:

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

$$\begin{cases} E(Q_{i2}|I = 2) = Z_i\alpha_2 + \sigma_2\lambda_2 \quad \text{(6a)} \\ \quad\vdots \qquad\qquad\qquad \vdots \\ E(Q_{ij}|I = J) = Z_i\alpha_j + \sigma_j\lambda_j \quad \text{(6b)} \end{cases}$$

Adopters, had they decided not to adopt (Counterfactual):

$$\begin{cases} E(Q_{i1}|I = 2) = Z_i\alpha_1 + \sigma_1\lambda_2 \quad \text{(7a)} \\ \quad\vdots \qquad\qquad\qquad \vdots \\ E(Q_{i1}|I = J) = Z_i\alpha_1 + \sigma_1\lambda_j. \quad \text{(7b)} \end{cases}$$

The values computed in Equations (6a) through (7b) are employed to generate unbiased causal effects. The ATEs are computed as the difference between Equations (6a) and (7a) or the difference between Equations (6b) and (7b). For instance, the difference between Equations (6a) and (7a) is specified as

$$ATT = E[Q_{i2}| = 2] - E[Q_{i1}|I = 2] = Z_i(\alpha_2 - \alpha_1) + \lambda_2(\sigma_2 - \sigma_1). \tag{8}$$

The initial specification on the right-hand side of Equation (8) would be the difference in adopters' average outcome if adopters' attributes had similar benefits as non-adopters, i.e., if adopters had similar attributes as non-adopters. The second part (λ_j) is the choice term that considers all the likely impacts of differences in the unobserved variables.

2.4 Multivalued inverse probability weighted regression adjustment

As mentioned previously, identification of the MESRM requires suitable instrumental variables and satisfying the exclusion restriction criterion which in empirical work, is not trivial. While we were able to find suitable instruments (see Section 2.2) following an admissibility test (Di Falco, Veronesi, and Yesuf 2011) – which has been widely employed to examine the suitability of instruments in many impact studies (e.g., Di Falco and Veronesi 2014; Ding and Abdulai 2020; Kiwanuka-Lubinda, Ng'ombe, and Machethe 2021), it does not mean that our instruments are perfect. Therefore, we complement our MESRM with the multivalued inverse probability weighted regression (MIPWR) model as a robustness check. The MIPWR model is doubly robust as it allows misspecification of one of the equations – the treatment status or outcome models. It accounts for selection bias from observed confounders. Essentially, the MIPWRA model employs the estimated inverse of the treatment probability weights to compute missing data-corrected regression estimates which are subsequently used to generate robust ATT estimates.

Following Linden et al. (2016) and Manda et al. (2021), the estimation of the MIPWR model involves two steps. First, a multinomial logit model is estimated to generate propensity scores for the adoption of combinations of multiple technologies as considered in this paper. At this point, the inverse of the probability of treatment weights is computed for each treatment combination. Second, outcome (hereafter, rice yield, gross rice income, and per capita consumption expenditure) regression models are estimated via weighted regression using the estimated weights for each treatment combination. It is in this stage where treatment-specific predicted outcomes for each observation are generated by using the estimated weighted regression coefficients. While these two steps are required, the empirical model is estimated in one step using generalised method of moments (GMM) whereby any potential estimation error from the estimated propensity scores is accounted for during the estimation of the standard errors. The MIPWRA-based ATTs for farm households that adopted multiple combinations of agricultural technologies are computed as

$$ATT_{\widetilde{Ji},\, \overrightarrow{J}} = E[(y_{\widetilde{Ji}} - y_{1i})|j = \overrightarrow{J}], \tag{9}$$

where $\widetilde{Ji}$ is the ith farm household's potential outcome (hereafter, rice yield, gross rice income, and per capita consumption expenditure) from the jth treatment combination (hereafter, chemical fertilisers, improved rice variety, and herbicides), $\widetilde{J}$ defines the treatment level of the treated potential outcome, 0 is the control potential outcome's treatment level, and $j = \overrightarrow{J}$ is a restriction to include only those respondents who receive the treatment level $\overrightarrow{J}$. To conserve space, we do not present all the details of the MIPWR (see Cattaneo 2010; Cattaneo, Drukker, and Holland 2013; Linden et al. 2016).

3. Data and descriptive statistics

The study utilises data from a farm household survey undertaken in Northern Ghana from October to December 2018. The sampled farm households were from the Northern, Upper East, and Upper West Regions of Ghana. The sample comprises 900 farm households with 300 from each region. A multistage sampling technique was employed in choosing the farm households. The first stage was a purposive selection of the Northern Zone of Ghana. The Northern Ghana was purposively selected because the zone constitutes the biggest rice-producing area in Ghana. The zone comprises the former Northern, Upper East and Upper West regions of Ghana. The second stage involved the selection of a district from each region based on their high level of rice production. The selected districts are Savelugu (Northern Region), Nadowli-Kaleo (Upper West) and Kassena Nankana East (Upper East). The third stage was a random selection of villages or communities from the operational areas of the Ministry of Food and Agriculture (MoFA). The final stage involved random selection of rice farm households from the different communities according to their size or the number of rice farm households in the various communities. The data collected included various rice production variables and characteristics of farm households in the study area using a structured questionnaire.

The selection of the variables for our empirical model resulted from reviewing various theoretical and empirical literature relating to adoption and impact evaluations (e.g., Khonje et al. 2018; Lu, Addai, and Ng'ombe 2021; Ng'ombe, Kalinda, and Tembo 2017; Teklewold et al. 2013). These studies identified numerous factors influencing adoption and, consequently, our outcome variables (rice yield, gross rice income, and per capita consumption expenditure) in their areas of interest. The factors considered here include household attributes (gender, age, years of schooling, household size), resource restrictions and market access (farm size, access to credit, land ownership, distance to market, farm distance, total livestock units), social capital, and network (extension contact), and production shocks (pest, disease, drought). Our outcome variables are rice yield, gross rice income, and per capita consumption expenditure. We, at the minimum, expect that adoption of an improved rice variety increases rice yield (Khonje et al. 2018; Villano et al. 2015), and therefore gross rice income (Kassie et al. 2015; Manda et al. 2020), and per capita consumption expenditure (Lu, Addai, and Ng'ombe 2021; Manda et al. 2019). We expect a similar pathway of the impacts from the use of chemical fertiliser among farmers as fertilisers would add nutrients such as Nitrogen (N) to the soil to improve plant growth and productivity (Donkor et al. 2016; Liverpool-Tasie 2017). With regards to the adoption of herbicides, most research focuses on labour savings and health concerns from herbicide use (Jallow et al. 2017; Lee and Thierfelder 2017). However, we expect herbicide use to reduce weeds on farm fields that would stimulate plant growth (due to reduced crop-weed competition for soil nutrients) and crop yield and potentially gross rice income (Chao et al. 2015), and per capita food consumption expenditure (Popp, Pető, and Nagy 2013).

Definitions and summary statistics of variables of the pooled sample are presented in Table 1. It is observed that the mean rice yield is 1434.78 kg/ha, while the gross rice income per hectare is GHS 3925.25.[1] Also, the average consumption expenditure per household is GHS 8.13. The treatment variables (i.e., agricultural technologies) comprising chemical fertiliser, improved rice variety, and herbicides had averages of 58%, 70%, and 39%, respectively. Of the sampled households, 68% had male heads, and their average age was 54.45 years. Most (89%) of the household heads were married with an average household size of 6.12, which is higher than Ghana's national average of 4.9. The average number of years of schooling of the household head is 3.02, which is low. This is likely to influence the adoption of agricultural technologies at the farm level. The average number of years of rice farming by household heads was 9.7.

The agricultural technologies considered in this study can be used in as many as eight possible combinations (2^3), presented in Table 2. Of the 900 farm household heads interviewed, 12.44% did not apply any agricultural technology ($C_0I_0H_0$) on their farms, while all the various technologies ($C_1I_1H_1$) were concurrently adopted by 21% of them. In all, 58.2% of the total sample adopted multiples of agricultural technologies during the production season. This reiterates the long adherence of most farmers to the use of single technologies in farming.

Descriptive statistics showing variable means according to technology combinations of usage (eight sub-categories of observations) are shown in Table 3. It can be observed that farm households that adopted agricultural technologies obtained relatively more rice yield and gross rice income and had higher per capita consumption expenditure than non-adopters. It can also be observed that most adopters of multiples of agricultural technologies are males, with their ages hovering between 40 to 45years. Besides, years of schooling of household heads who adopted multiples of technologies are averagely higher than single adopters and non-adopters. Larger households adopted all three agricultural technologies during the rice production season. Adopters of multiples

Table 1. Definition and summary statistics of the pooled sample.

Variables	Description	Pooled sample Mean	SD
Outcome			
Rice yield	Rice yield in kg/ha	1434.78	1160.96
Gross rice income	Gross rice income in GHS	3925.36	5101.30
Per capita consumption expenditure	Total food consumption per household member in GHS	8.13	11.44
Treatment/agrochemicals			
Chemical fertiliser	1 if household head applies a chemical fertiliser, 0 otherwise	0.58	0.49
Improved rice variety	1 if household head adopted improved rice variety, 0 otherwise	0.70	0.46
Herbicide	1 if household head applies herbicide, 0 otherwise	0.39	0.49
Socio-economic characteristics			
Gender	1 if household head is a male, 0 otherwise	0.68	0.47
Age	Age of household head in years	42.45	9.82
Marital status	1 if married, 0 otherwise	0.89	0.31
Years of schooling	Years of formal education of the household head	3.02	4.50
Household size	Number of household members	6.12	2.02
Years of rice farming	Years of rice farming	9.70	5.43
Resource constraints/institutional factors			
Farm size	Total rice farm size in hectares	0.64	0.54
Total livestock	Total livestock units	45.00	44.44
Credit access	1 if the household head had access to credit, 0 otherwise	0.33	0.47
Market distance	Distance from farm to market in km	4.07	2.05
Farm distance	Distance from home to the farm in km	3.99	2.36
Extension access	1 if the household head had access to extension service, 0 otherwise	0.39	0.49
Market information	1 if the household head had access to market information, 0 otherwise	0.72	0.45
Land ownership	1 if household head is the landowner, 0 otherwise	0.54	0.50
Production shocks			
Pest	1 if there was a pest outbreak, 0 otherwise	0.46	0.50
Disease	1 if there was disease outbreak, 0 otherwise	0.66	0.47
Drought	1 if there was a drought, 0 otherwise	0.75	0.43

of agricultural technologies have increased access to market information. Most (65%) landowners did not adopt any of the agricultural technologies. Thirty-two percent of household heads who had access to credit did not adopt any technology, while 34% of their counterparts adopted all the technologies.

Household heads with longer market distances adopted multiples of agricultural technologies. About 63% of households that had access to extension services adopted all the agricultural technologies. Adoption of a combination of all the three technologies is higher in households that witnessed shocks such as pest (50%), disease (50%), and drought (65%). While simple comparisons of differences in outcome variables between adopters and non-adopters of agricultural technologies shown in the upper rows of Table 3 are often considered as evidence of causal effects, they are

Table 2. Farmers' agricultural technology usage packages.

Choice (*j*)	Agricultural technology usage package	Chemical fertiliser C_1	Chemical fertiliser C_0	Improved rice variety I_1	Improved rice variety I_0	Herbicides H_1	Herbicides H_0	Frequency	Percent
1	$C_0\ I_0\ H_0$		√		√		√	112	12.44
2	$C_1\ I_0\ H_0$	√			√		√	50	5.56
3	$C_0\ I_1\ H_0$		√	√			√	147	16.33
4	$C_0\ I_0\ H_1$		√		√	√		67	7.44
5	$C_1\ I_1\ H_0$	√		√			√	242	26.89
6	$C_1\ I_0\ H_1$	√			√	√		45	5.00
7	$C_0\ I_1\ H_1$		√	√		√		48	5.33
8	$C_1\ I_1\ H_1$	√		√		√		189	21.00

Note: Each component in the combination packages entails a binary variable for agricultural technologies combination. Chemical fertiliser (C), Improved rice variety (I), and Herbicides (H). Where the subscript denotes 1 = if adopted and 0 = otherwise.

Table 3. Summary statistics by combinations of agricultural technologies.

	Mean values of agricultural technology combinations							
Variables	$C_0\ I_0\ H_0$	$C_1\ I_0\ H_0$	$C_0\ I_1\ H_0$	$C_0\ I_0\ H_1$	$C_1\ I_1\ H_0$	$C_1\ I_0\ H_1$	$C_0\ I_1\ H_1$	$C_1\ I_1\ H_1$
Outcome								
Rice yield	513.73	747.28	857.18	599.30	1953.61	1411.81	967.27	2367.79
Gross rice income	663.08	2142.67	1711	837.24	5777.58	3784.11	1456.53	7436.18
Per capita consumption expenditure	4.85	11.02	6.71	3.79	8.68	9.68	7.35	11.07
Socio-economic factors								
Gender	0.69	0.58	0.72	0.82	0.62	0.80	0.67	0.68
Age	45.25	42.10	44.07	45.49	40.84	40.76	43.04	40.86
Marital status	0.81	0.88	0.95	0.90	0.91	0.87	0.79	0.90
Years of schooling	2.69	2.44	3.27	2.81	2.52	2.80	4.27	3.60
Household size	5.96	5.96	6.34	6.06	6.12	5.93	5.73	6.25
Years of rice farming	10.63	9.94	9.02	12.24	9.33	9.67	9.31	9.31
Resource constraints/Institutional factors								
Farm size	0.34	0.59	0.51	0.30	0.84	0.68	0.42	0.85
Total livestock	42.26	48.60	47.90	56.58	41.31	45.64	47.65	43.20
Credit access	0.32	0.36	0.31	0.36	0.31	0.38	0.35	0.34
Market distance	2.78	3.60	3.42	2.94	4.83	4.66	3.83	4.80
Farmstead distance	2.54	2.90	3.29	2.27	5.05	3.40	3.71	5.13
Extension access	0.13	0.36	0.23	0.12	0.54	0.36	0.13	0.63
Market information	0.39	0.50	0.66	0.37	0.90	0.86	0.63	0.92
Land ownership	0.65	0.44	0.63	0.61	0.50	0.44	0.64	0.45
Shocks								
Pest	0.34	0.58	0.39	0.36	0.54	0.27	0.44	0.50
Disease	0.70	0.68	0.75	0.75	0.70	0.52	0.67	0.50
Drought	0.67	0.80	0.82	0.75	0.82	0.73	0.69	0.65

Note: A means of comparison of the explanatory variables between each agricultural technology combination (adopters) and non-adopters ($C_0\ I_0\ H_0$) under the assumption of equal variance

more often than not, misleading as they do not take into account of any potential confounders (Angrist and Pischke 2015). A more rigorous analysis of these impacts is discussed in Section 4.0.

4. Empirical results and discussion

4.1 Conditional and unconditional probabilities of usage of agricultural technologies

The sample conditional and unconditional probabilities are presented in Table 4. On average, chemical fertiliser, improved rice variety, and herbicides were used by 58.44%, 69.56%, and 38.78% of the farm households. The existence of interdependence across the three agricultural technologies is also emphasised. The conditional probability of improved rice variety adoption by farm households increased from 69.56% to 80.11% when farm household heads adopted chemical fertilisers. Similarly, farm household heads' conditional probability of adopting herbicides rose from 38.78 to 71.22% when selecting chemical fertilisers and 82% when jointly used with improved rice variety. These results show complementarity in the adoption of agricultural technologies by farm household heads.

Table 4. Sample conditional and unconditional adoption probabilities of technologies (%).

	Chemical fertiliser (*C*)	Improved rice variety (*I*)	Herbicides (*H*)
$P(Y_k = 1)$	58.44	69.56	38.78
$P(Y_k = 1 \mid Y_C = 1)$	100	80.11	71.22
$P(Y_k = 1 \mid Y_I = 1)$	80.1	100	82
$P(Y_k = 1 \mid Y_H = 1)$	71.22	82	100
$P(Y_k = 1 \mid Y_C = 1, Y_I = 1)$	100	100	65.67
$P(Y_k = 1 \mid Y_C = 1, Y_H = 1)$	100	74.56	100
$P(Y_k = 1 \mid Y_I = 1, Y_H = 1)$	63.78	100	100

Note: Y_k is a binary variable indicating the adoption status of agricultural technologies concerning selection *k* (Chemical Fertiliser (*C*), Improved Rice Variety (*I*) and Herbicides (*H*)). The comparison is among unconditional probabilities and conditional probabilities in individual agricultural technologies.

4.2 Determinants of the choice of selection of combinations of agricultural technologies

The estimates of the multinomial logit model are presented in Table 5. The base category is the non-adoption of agricultural technologies ($C_0I_0H_0$). The Wald test to check whether all regression coefficients are jointly equal to zero is rejected [$\chi^2(119) = 429.34$; $p = 0.000$], indicating that the multinomial logit model had strong explanatory power and fitted the data reasonably well. Nguyen-Van, Poiraud, and To-The (2017) asserted that the marginal effects present a good picture and meaning regarding the magnitudes of impact on individual probability models. The findings show that the marginal effects vary across the various technology combinations.

Gender of the household heads has a positive and significant effect on the adoption of the combination $C_1I_0H_1$. More specifically, male-headed farm households are more likely to adopt a combination of chemical fertiliser and herbicides than female-headed farm households, all other factors held constant. Plausibly, this could be because male-headed farm households are usually more resourceful among rural households and have more capacity to acquire chemical fertiliser and herbicides. This finding is consistent with Gebre et al. (2019).

Age of a household head has a positive and statistically significant influence on the adoption of the combination $C_0I_1H_0$. Specifically, an increase in the household head's age is associated with increased likelihood of adopting improved rice seeds, *ceteris paribus.* This finding corroborates with the findings of Wordofa et al. (2021) who report similar findings in Eastern Ethiopia. As in Wordofa et al. (2021), this results could be due to the build-up of farmer experience, knowledge, and physical and social capital. Marital status has a positive and significant impact on the adoption of the combination $C_0I_1H_0$. This finding suggests that farm household heads that are married are more likely than their unmarried counterparts to adopt improved rice varieties. As expected, marriage is associated with an increase in family size, which implies more household members to feed and therefore, the need to adopt improved technologies to boost crop productivity and sufficient food. However, this finding contradicts Ojo et al. (2021), who indicate that single farmers have fewer responsibilities than married individuals which makes the former to more likely channel their resources to adopting agricultural technologies.

The variable years of schooling has a negative and statistically significant influence on the household head's decision to adopt $C_1I_1H_0$. Thus, an increase in the number of years that household heads spent on education by a year is associated with a reduction in the likelihood to use chemical fertilisers and improved seed. This contradicts the findings of Gebremariam and Tesfaye (2018), who indicated that households with better education are expected to be more aware of the benefits of new technologies. Moreover, years of rice farming have a positive and significant effect on the adoption of the combination C_0 I_0 H_1 which implies that an additional year of experience in rice farming is associated with an increased probability of adopting herbicides, everything else held constant. This may be because an increase in years of rice farming is associated with a wealth of experiences, lessons, and knowledge gain – which would boost farmer's confidence in the herbicides and therefore, their probability of adopting them. On the contrary, years of rice farming of household heads negatively impact adopting the combination $C_0I_1H_0$. Specifically, as the number of years of farming rice by household heads increases by a year, it leads to a decline in their likelihood to adopt $C_0I_1H_0$, *ceteris paribus.* This is likely to be the situation as most experienced farmers tend to be conservative, especially when it comes to adopting new agricultural technologies in which they lack experience (Somda et al. 2002).

Farm size has a positive and significant influence on the probability of adopting the combinations $C_1I_0H_0$, $C_1I_1H_0$, and $C_1I_0H_1$. More specifically, increasing farm size by a hectare is associated with an increased likelihood of adopting chemical fertilisers, a chemical fertiliser and improved rice package, and a combination of chemical fertilisers and herbicides. Plausibly, farmland has sometimes been used as an indicator of wealth, and households' having large farm sizes will likely adopt agricultural technologies. This is consistent with Anang and Amikuzuno (2015) findings, which report a similar result among rice farmers in Northern Ghana. On the other hand, we find that farm size negatively

Table 5. Multinomial logit model marginal effects for the selection of various combinations of agricultural technologies.

	C_1 I_0 H_0		C_0 I_1 H_0		C_0 I_0 H_1		C_1 I_1 H_0		C_1 I_0 H_1		C_0 I_1 H_1		C_1 I_1 H_1	
Variable	d*y*/d*x*	SE	d*y*/d*x*	SE	d*y*/d*x*	SE	d*y*/d*x*	SE	d*y*/d*x*	SE	d*y*/d*x*	SE	d*y*/d*x*	SE
Gender	−0.020	0.015	−0.007	0.027	0.032	0.021	−0.041	0.030	0.033*	0.019	0.004	0.017	0.025	0.028
Ln (Age)	−0.052	0.035	0.150**	0.057	0.010	0.040	−0.059	0.064	−0.049	0.032	−0.012	0.034	−0.024	0.057
Marital status	−0.007	0.024	0.140**	0.051	0.018	0.029	−0.024	0.049	−0.030	0.023	−0.034	0.021	−0.024	0.046
Ln (Years of schooling)	−0.011	0.008	0.012	0.012	0.004	0.008	−0.032**	0.014	−0.009	0.007	0.016	0.007	0.019	0.012
Ln (Household Size)	−0.014	0.021	0.045	0.034	−0.025	0.024	0.005	0.039	−0.004	0.020	−0.027	0.022	0.042	0.035
Ln (Years of rice farming)	−0.007	0.015	−0.062**	0.024	0.036*	0.018	0.043	0.031	−0.007	0.015	−0.009	0.016	0.022	0.028
Ln (Farm size)	0.034**	0.014	−0.002	0.021	−0.048**	0.017	0.055**	0.025	0.034**	0.013	−0.035**	0.014	0.024	0.022
Ln (Total livestock)	0.008	0.011	−0.012	0.015	0.030**	0.013	0.002	0.019	−0.008	0.009	0.015	0.010	−0.030*	0.016
Credit access	0.010	0.015	−0.012	0.026	0.010	0.017	−0.020	0.029	0.012	0.014	0.006	0.015	0.002	0.026
Ln (Market distance)	0.011	0.016	−0.056**	0.027	−0.024	0.021	0.094**	0.030	0.040**	0.016	−0.002	0.017	0.035	0.027
Ln (Farm Distance)	−0.061**	0.020	−0.029	0.032	−0.007	0.027	0.070**	0.034	−0.078***	0.020	0.043**	0.020	0.045	0.030
Land ownership	−0.022	0.015	0.040	0.024	0.001	0.017	0.005	0.027	−0.017	0.014	0.006	0.015	−0.039	0.025
Pest	0.027*	0.015	−0.030	0.024	−0.021	0.017	0.098***	0.028	−0.036**	0.016	−0.001	0.015	0.006	0.026
Disease	0.008	0.017	0.057**	0.028	0.010	0.020	0.041	0.032	−0.025	0.016	0.010	0.017	−0.096**	0.028
Drought	0.002	0.019	0.058*	0.031	0.002	0.020	0.078**	0.038	−0.007	0.018	−0.005	0.017	−0.089**	0.031
Extension access	0.017	0.016	−0.057**	0.028	−0.035	0.025	0.027	0.028	−0.004	0.014	−0.058**	0.022	0.144***	0.025
Market information	−0.055**	0.020	0.003	0.032	−0.0152	0.021	0.038	0.050	0.026	0.023	−0.012	0.020	0.060	0.049

Note: d*y*/d*x* and SE designate marginal effect and standard errors respectively; ***, **, and * indicate statistical significance at 1%, 5%, and 10% level; C_0 I_0 H_0 is the reference category of non-adoption of agricultural technologies affects household heads' likelihood to adopt $C_0I_0H_1$ and $C_0I_1H_1$. An increase in farm size by a hectare is associated with a reduction in the probability to adopt the combinations $C_0I_0H_1$ and $C_0I_1H_1$, everything else held constant. This could be due to farmers' inability to meet the cost of these technologies, as more capital would be required to invest in these technologies and be used on extra land available. These results are consistent with Yigezu et al. (2018), who indicate that a key determining factor of adoption of technologies by smallholders is the high initial investment. This deviates from the idea that some agricultural technologies are scale-dependent due to the relevance of farm size in their adoption.

Adoption of $C_0I_0H_1$ is positively influenced by total livestock unit ownership by the farm household. A unit increase in the total livestock owned by household heads leads to an increase in the likelihood of the adoption of herbicides by smallholder farmers in the sample. Livestock is also a source of draught power for agricultural practices such as ploughing (Ng'ombe et al. 2014), resulting in increased farmed land. It is possible to use livestock as an instrument for acquiring these technologies that require cash. For example, Khonje et al. (2015) report that farmers who own assets could either change them to liquid cash or use them as a guarantee to acquire credit to procure farm inputs such as chemical fertiliser, insecticides, and herbicides for production. On the contrary, total livestock units owned by households negatively and significantly influence the adoption of the combination $C_1I_1H_1$. Specifically, relative to the base category of non-adoption, a unit increase in total livestock unit is associated with a decrease in the probability of adopting a combination of chemical fertilisers, improved rice varieties and herbicides simultaneously, everything else constant. This could result when farm households consider their livestock as sacred animals that need to be used only for social purposes such as religious celebrations, or in cases when there are no oxen to use for draught power, among others, instead of being used as an instrument to obtain credit (Yaro and Hesselberg 2010).

Distance to markets has a positive and significant influence on the adoption of the combinations $C_1I_1H_0$ and $C_1I_0H_1$. This result means that the longer the farmers' homesteads are from the agricultural market, the more likely farmers would on average adopt chemical fertilisers and improved rice varieties, and a combination of chemical fertilisers and herbicides. This result is unexpected and contradicts the findings of Anang and Amikuzuno (2015). Anang and Amikuzuno (2015) find that an increase in market distance is expected to increase the transaction costs due to long- distance travel – which is likely to decrease technology adoption in agriculture. Moreover, market distance is associated with a decrease in the likelihood of farmers to adopt the combination $C_0I_1H_0$. Consistent with Anang and Amikuzuno (2015), this could be because of the high transaction cost involved in acquiring improved seeds from a distant market centre.

Our results further show that the distance between farmers' homesteads and their farmland negatively influences farmers' likelihood of adopting the combinations $C_1I_0H_0$ and $C_1I_0H_1$. More specifically, compared with the base category of non-adoption of technology, an increase in the distance from household heads' homestead to their farmland reduces the likelihood of the adoption of chemical fertiliser ($C_1I_0H_0$) and a combination of chemical fertiliser and herbicides ($C_1I_0H_1$). This could plausibly be due to the drudgery involved in carrying such technologies to a far distance to use them on the farm (Khonje et al. 2018). On the other hand, farm distance to farmsteads also positively influences the adoption of $C_1I_1H_0$ and $C_0I_1H_1$, a finding that indicates that increased distance between a farmer's homestead and their farmlands increases the likelihood of adopting a combination of chemical fertilisers and improved rice varieties, and improved rice varieties and herbicides among smallholder farmers. Plausibly, this may be when farmers consider the returns from the technology use to outweigh the drudgery costs linked with handling them.

With regard to pest infestation, results show that farm households whose fields experience pest infestation are more likely to adopt a combination of $C_1I_0H_0$ and $C_1I_1H_0$. This is consistent with the findings of Teklewold et al. (2013), who show that pest stress increases the adoption of such agricultural technologies. However, this may not work across the board, as our results suggest that pest stress negatively influences the adoption of $C_1I_0H_1$, highlighting heterogeneous effects by factors that affect the adoption of agricultural technologies among smallholder farmers.

Furthermore, weather shocks such as drought exposure negatively influence the adoption of the combination of $C_1I_1H_1$. Specifically, we found that farm households exposed to droughts during rice production seasons are less likely to adopt agricultural technology comprising chemical fertilisers, improved rice varieties, and herbicides. This result is consistent with Wainaina, Tongruksawattana, and Qaim (2016), who contend that droughts negatively influence the adoption of agricultural technologies in Kenya. The reason behind our finding could be that farmers decide not to apply chemical fertilisers complementary with improve rice varieties and herbicides in a drought-stressed season because chemical fertilisers require moisture for increased nitrogen use efficiency by plants. However, further results show that drought positively influences rice farmers' probability to adopt $C_1I_1H_0$ and $C_1I_1H_0$. This could be because such a mixture of technologies has previously yielded desirable payoffs in a drought season. Alternatively, the Northern Ghana is located along the Sahel zone of Africa and experiences erratic rainfall patterns. Therefore, as a risk-averse mechanism, farmers may adopt drought-resistant varieties to cushion likely output reduction by adopting nutrient-adding soil technologies during the farming season.

Access to extension services positively and significantly influences the adoption of $C_1I_1H_1$ but negatively affects the adoption of $C_0I_1H_0$ and $C_0I_1H_1$. Particularly, smallholder farm households with access to extension services are more likely to adopt a combination of all agricultural technologies (i.e., chemical fertiliser, improved rice variety, and herbicides) but do negatively affect the adoption of $C_0I_1H_0$ and $C_0I_1H_1$. These findings are consistent with Khonje et al. (2015) and Ng'ombe, Kalinda, and Tembo (2017) who contend that farmers who receive extension visits and/or may be exposed to field events and demonstration trials have a high likelihood to adopt agricultural technologies comprehensively. This could be because they become more informed and aware of the benefits associated with such technologies. As in Ng'ombe, Kalinda, and Tembo (2017), these results highlight an important message that government extension services encourage a more comprehensive adoption portfolio of agricultural technologies than otherwise. For farmers' access to market information, results show that smallholder farm households with access to market information are less likely to adopt $C_1I_0H_0$ than otherwise. This is contrary to our theoretical expectations but it is worth to mention that if rice producers have access to available market information, it may reduce the high transaction costs associated with information acquisition on agricultural inputs and products. This would be expected to increase the likelihood of adopting these agricultural technologies (Mutenje et al. 2016).

4.3 Impact of multiple agricultural technology combinations on household welfare

Table 6 shows the multinomial endogenous switching regression (MESR)-based causal effects of adopting multiple agricultural technologies on farm household welfare indicators – rice yield, gross rice income, and per capita consumption expenditure.[2] As a robustness check of causal effects from the MESR model, we applied the multivalued inverse probability weighted regression (MIPWR) model. The results in column (3) show technology impacts on rice yield in kilograms per hectare. The unconditional average effect results indicate that adoption of all agricultural combinations considered here has positive and significant causal effects on rice yields relative to non-adoption. The agricultural technology combination that results in the lowest rice yield per hectare (i.e., 284 kg/ha) is adoption of herbicides (i.e., $C_0I_0H_1$) while adoption of chemical fertilisers and herbicides together (i.e., $C_1I_0H_1$) leads to the highest impacts on rice yields (i.e., 7,172,379 kg/ha). Generally, these findings are consistent with previous literature on crop yield returns from input intensification (e.g., Kassie et al. 2018; Wossen et al. 2019b).

Column (4) of Table 6 shows the unconditional average effects of the seven combinations of agricultural technologies on gross rice income in Ghanaian Cedis. The results are similar to those in column 3. That is, all the technology packages significantly and positively impact gross rice

Table 6. Average treatment effect results based on the multinomial endogenous switching regression model.

Adoption effects	Combination	Rice yield (kg/ha)	Gross rice income (GHS)	Per capita consumption expenditure
Unconditional average effect	$C_1I_0H_0$	347.632*** (22.213)	895.302*** (68.309)	1.269** (0.508)
	$C_0I_1H_0$	458.307*** (24.107)	1353.135*** (98.627)	−2.620*** (0.303)
	$C_0I_0H_1$	283.833*** (22.076)	1062.543*** (121.017)	−0.508 (0.342)
	$C_1I_1H_0$	914.275*** (27.319)	2464.65*** (100.473)	−0.967** (0.354)
	$C_1I_0H_1$	7171.994*** (2131.567)	14,921.4*** (3711.259)	7.960*** (0.822)
	$C_0I_1H_1$	285.186*** (27.068)	680.901*** (89.271)	3.496*** (0.498)
	$C_1I_1H_1$	1052.727*** (30.941)	3311.377*** (155.488)	0.499 (0.412)
Average treatment effects on treated (ATT)	$C_1I_0H_0$	324.880*** (70.407)	435.510** (105.225)	4.905*** (1.053)
	$C_0I_1H_0$	115.907** (36.174)	212.579** (73.235)	1.353** (0.353)
	$C_0I_0H_1$	102.164** (31.139)	292.826* (148.976)	0.453 (0.380)
	$C_1I_1H_0$	332.385*** (54.187)	552.860*** (111.373)	5.820*** (0.639)
	$C_1I_0H_1$	3464.411** (1479.17)	7099.387** (3557.824)	21.868*** (3.612)
	$C_0I_1H_1$	143.501** (51.850)	193.741** (94.074)	2.522***(0.639)
	$C_1I_1H_1$	339.806*** (50.450)	683.046*** (160.788)	9.780*** (1.067)

Note: Standard errors are in parenthesis; ***, ** and * indicate statistical significance at 1%, 5% and 10% level.

income. While the adoption of $C_1I_0H_1$ results in most gross rice income (in terms of unconditional average effects) amongst all the possible combinations of technologies, as it is for rice yield per hectare, $C_0I_1H_1$ yields the lowest gross rice income rather than $C_0I_0H_1$ – which demonstrates heterogeneous unconditional average effects by outcome variable. Column (5) of Table 6 shows unconditional average effects of adopting the combinations of agricultural technologies on per capita consumption expenditure among our sample in Northern Ghana. The unconditional effects indicate that the combinations $C_1I_0H_0$, $C_1I_0H_1$, and $C_0I_1H_1$ positively and significantly impacts household consumption expenditure, whereas $C_0I_1H_0$ and $C_1I_1H_0$ lead to a reduction in per capita consumption expenditure.

A clearer picture of the impacts of adopting agricultural technologies is one that accounts for both observed and unobserved factors – the average treated effects on the treated (ATT) findings shown below the unconditional average effects. Similarly, it can be observed that the adoption of all the packages positively and significantly impact rice yield. The ATTs confirm the earlier results with the adoption of a combination of chemical fertiliser and herbicides leading to 3464 kg/ha while adoption of herbicides leads to the least rice yields (i.e., 102 kg/ha). Regarding the ATT with respect to gross rice income, results indicate positive causal effects of all technology combinations. This is consistent with the findings of Khonje et al. (2018) and Teklewold et al. (2013). The ATTs of all the combinations except $C_0I_0H_1$ had a positive and significant impact on per capita consumption expenditure with a combination of chemical fertilisers and herbicides yielding the most payoff in this category once again.

In general, the ATT results are lower in magnitude than the unconditional average effects shown in Table 6. Unconditional average effects may be misleading, reason is that effects from observed and unobserved confounders are unaccounted for. With ATTs, such confounding effects are accounted for thereby leading to lower values of causal effects than in the case of unconditional average effects. For example, the impact of adopting a package of chemical fertiliser and herbicides is overstated by 52.4% under unconditional average effects. This implies that using the MESRM model was appropriate and that its identification was credible.

4.4 Robustness checks

As discussed before, we used the MIPWR for robustness check of the MESR model results. Our MIPWR-based ATT results based on Equation (9) are shown in Table 7. It can be observed that the adoption of all combinations of technologies considered in this study improves rice yields, gross

Table 7. Average treatment effect results from the multivalued inverse probability weighted regression model.

Combination	Treatment effects	Rice yield (kg/ha)	Gross rice income (GHS) per hectare	Per capita consumption expenditure
$C_1I_0H_0$	ATT	971.750*** (125.724)	3447.900*** (441.893)	6.427*** (0.591)
$C_0I_1H_0$	ATT	1098.118*** (124.055)	2753.897*** (568.217)	11.092*** (0.926)
$C_0I_0H_1$	ATT	760.630*** (132.791)	1777.916*** (476.601)	6.251*** (0.645)
$C_1I_1H_0$	ATT	1823.982*** (78.925)	4653.555*** (223.817)	8.032*** (0.510)
$C_1I_0H_1$	ATT	1678.296*** (142.476)	3951.506*** (406.473)	6.392*** (0.607)
$C_0I_1H_1$	ATT	858.469*** (103.222)	2935.485*** (158.324)	6.769*** (1.284)
$C_1I_1H_1$	ATT	2008.992*** (110.933)	5251.320*** (255.762)	7.102*** (0.442)

Note: SE in brackets are robust standard errors; ***, **, and * denote statistical significance at 1%, 5%, and 10% level.

rice income and per capita consumption among farmers in Northern Ghana. Results show that $C_1I_1H_1$ results in the highest rice yields and gross rice income though the adoption of improved rice varieties leads to highest per capita consumption expenditure. Adoption of herbicides alone leads to lowest rice yields, gross rice income and per capita consumption expenditure among all the combinations considered. The general take-home message from results in Table 7 is that on average, agricultural technologies adopted in combination result in higher rice yields, gross rice income and per capita consumption expenditure. Of important notice is that the MIPWR-based ATTs reported in Table 7 are quantitatively higher than those from MESRM. As in Manda et al. (2021), and Gormley and Matsa (2014), this is because matching-based estimators merely account for observed heterogeneity thereby exposing results to unobserved heterogeneity. Zhou and Xie (2014) also showed that propensity score-related methods and marginal treatment effects methods of causal inference might produce different estimates due to how their estimates are derived, which is also a potential explanation to our results. However, the two findings are generally consistent which provides confidence in our MESRM model specifications.

5. Conclusions and policy implications

The adoption of multiple agricultural technologies and assessing the likely impacts on household welfare has received considerable attention from various stakeholders in agriculture among different countries. Due to the adoption of single technologies, poor application rates have been recorded despite significant investment in promotions to encourage their multiple adoptions. Using cross-sectional data from rice-producing households in Northern Ghana, we examine the impacts of adopting unique combinations of agricultural technologies on household welfare outcomes. We employ the multinomial endogenous switching regression model (MESRM) to correct for potential selection bias from observed and unobserved confounders. As a robustness check, we also employed the multivalued inverse probability regression (MIPWR) model – a doubly-robust model that allows misspecification of one of the equations – the treatment status or outcome models.

The multinomial logit model results indicated that the likelihood of adopting diverse combinations of agricultural technologies is affected by various socio-economic attributes, resource constraints, institutional factors, and production shocks. These findings can be used to make informed and targeted policies meant to scale up adoption rates of multiple and inter-related rice production technologies. For instance, farm size significantly influences the adoption of various agricultural technologies, contributing to the ongoing debate on farm size structural change and technology use on environmental sustainability. The statistical significance of access to market information at influencing adoption suggests the need to improve information flow among players and stakeholders in the agricultural supply and marketing chain. Moreover, while access to extension services negatively influences the adoption of some of these technology combinations, it strongly and positively influences the adoption of combinations of all the technologies. The reason could be that extension services may be more focused on a comprehensive adoption of all the available improved agricultural technologies to farmers, especially as our results and most previous research (e.g., Khonje et al. 2018; Ng'ombe, Kalinda, and Tembo 2017; Teklewold et al. 2013) shows that adoption of technologies in combination in lieu of adopting them singly results in more economic payoffs.

Regarding household welfare impact of multiple agricultural technology adoption, the conclusion is that the adoption of agricultural technologies, on average, improves rice yields, gross rice income, and household per capita consumption expenditure. Most importantly, the adoption of a combination of chemical fertilisers and improved rice variety, and herbicides significantly improved households' rice yields, gross rice income per hectare, and per capita consumption expenditure. Based on these results, we recommend policies that focus on increased adoption of these agricultural technologies in combination through increased extension access in Northern Ghana. Most importantly, our results recommend more adoption of these agricultural technologies in combination rather than singly to help farm households realise the most benefits from the essential synergistic effects between agricultural production technologies in Northern Ghana and other developing areas in Africa.

A limitation of the study is that the data used is at the household level, as plot-level data is non-existent. Yield regressions are better estimated at the plot level and using separate plot-level and household-level explanatory variables. Moreover, this study relies on rice production data from one rice cropping year. Similar analyses but based on aggregate rice production (production over different rice cropping years) or richer panel data with more agricultural technologies and outcome variables is an interesting area for future research.

Notes

1. US Dollars (USD) to Ghanaian Cedis (GHS) exchange rate for December 31, 2018. 1USD: 4.9GHS
2. The second step of the regression estimation is not presented to save space. However, these results are available upon request

Disclosure statement

No potential conflict of interest was reported by the author(s).

Data availability statement

Data will be available on a reasonable request from the corresponding author.

ORCID

Kwabena Nyarko Addai http://orcid.org/0000-0001-6757-8155
John N. Ng'ombe http://orcid.org/0000-0002-1410-1350

References

Altieri, M.A., and V.M. Toledo. 2011. The agroecological revolution in Latin America: Rescuing nature, ensuring food sovereignty and empowering peasants. *Journal of Peasant Studies* 38: 587–612.

Anang, B.T., and J. Amikuzuno. 2015. Factors influencing pesticide use in smallholder rice production in Northern Ghana. *Agriculture, Forestry and Fisheries* 4: 77.

Angrist, J.D., and J.-S. Pischke. 2015. *Mastering metrics – the path from cause to effect*. New Jersey: Princeton University Press.

Barrios, S., L. Bertinelli, and E. Strobl. 2010. Trends in rainfall and economic growth in Africa: A neglected cause of the African growth tragedy. *Review of Economics and Statistics* 92: 350–66.

Becerril, J., and A. Abdulai. 2010. The impact of improved maize varieties on poverty in Mexico: A propensity score-matching approach. *World Development* 38: 1024–35.

Biru, W.D., M. Zeller, and T.K. Loos. 2019. The impact of agricultural technologies on poverty and vulnerability of smallholders in Ethiopia: A panel data analysis. *Social Indicators Research* 147: 1–28.

Borlaug, N. 2007. Feeding a hungry world. *Science* 318: 359.
Bourguignon, F., M. Fournier, and M. Gurgand. 2007. Selection bias corrections based on the multinomial logit model: Monte Carlo comparisons. *Journal of Economic Surveys* 21: 174–205.
Cattaneo, M.D. 2010. Efficient semiparametric estimation of multi-valued treatment effects under ignorability. *Journal of Econometrics* 155: 138–54.
Cattaneo, M.D., D.M. Drukker, and A.D. Holland. 2013. Estimation of multivalued treatment effects under conditional independence. *The Stata Journal* 13: 407–50.
Chamberlain, G., and Z. Griliches. 1975. Unobservables with a variance-components structure: Ability, schooling, and the economic success of brothers. *International Economic Review* 16: 422–49.
Chao, Z., G. Shi, S. Jian, H.U. Rui-fa, C. Zhang, S. Guanming, J. Shen, et al. 2015. Productivity effect and overuse of pesticide in crop production in China. *Journal of Integrative Agriculture* 14: 1903–10.
Danso-Abbeam, G., and L.J.S. Baiyegunhi. 2018. Welfare impact of pesticides management practices among smallholder cocoa farmers in Ghana. *Technology in Society* 54: 10–9.
Di Falco, S., and M. Veronesi. 2014. Managing environmental risk in presence of climate change: The role of adaptation in the Nile basin of Ethiopia. *Environmental and Resource Economics* 57: 553–77.
Di Falco, S., M. Veronesi, and M. Yesuf. 2011. Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. *American Journal of Agricultural Economics* 93: 825–42.
Diao, X., P. Hazell, and J. Thurlow. 2010. The role of agriculture in African development. *World Development* 38: 1375–83.
Ding, Z., and A. Abdulai. 2020. An analysis of the factors influencing choice of microcredit sources and impact of participation on household income. *Journal of International Development* 32: 505–25.
Donkor, E., E. Owusu-Sekyere, V. Owusu, H. Jordaan, D. Emmanuel, E. Owusu-Sekyere, V. Owusu, and H. Jordaan. 2016. Impact of agricultural extension service on adoption of chemical fertilizer: Implications for rice productivity and development in Ghana. *NJAS – Wageningen Journal of Life Sciences* 79: 41–9.
Dubin, J.A., and D.L. McFadden. 1984. An econometric analysis of residential electric appliance holdings and consumption. *EconometricA* 52: 345.
FAO. 2018. "FAO's Work on Agricultural Innovation." 13.
Gebre, G.G., H. Isoda, D.B. Rahut, Y. Amekawa, and H. Nomura. 2019. Gender differences in the adoption of agricultural technology: The case of improved maize varieties in southern Ethiopia. *Women's Studies International Forum* 76: 102264.
Gebremariam, G., and W. Tesfaye. 2018. The heterogeneous effect of shocks on agricultural innovations adoption: microeconometric evidence from rural Ethiopia. *Food Policy* 74: 154–61.
Gormley, T.A., and D.A. Matsa. 2014. Common errors: How to (and not to) control for unobserved heterogeneity. *The Review of Financial Studies* 27: 617–61.
Holt-Giménez, E., A. Shattuck, M. Altieri, H. Herren, and S. Gliessman. 2012. We already grow enough food for 10 billion people and still can't end hunger. *Journal of Sustainable Agriculture* 36: 595–8.
Jallow, M.F.A., D.G. Awadh, M.S. Albaho, V.Y. Devi, and B.M. Thomas. 2017. Pesticide risk behaviors and factors influencing pesticide use among farmers in Kuwait. *Science of the Total Environment* 574: 490–8.
Jhamtani, H. 2011. *The Green Revolution in Asia: lessons for Africa*. Ed. Lim Li. Rome: FAO..
Julien, J.C., B.E. Bravo-Ureta, and N.E. Rada. 2019. Assessing farm performance by size in Malawi, Tanzania, and Uganda. *Food Policy* 84: 153–64.
Juma, C. 2013. The New harvest: AGRICULTURAL innovation in Africa by Calestous Juma. *Science and Public Policy* 40: 817–8.
Kassie, M., P. Marenya, Y. Tessema, M. Jaleta, D. Zeng, O. Erenstein, and D. Rahut. 2018. Measuring farm and market level economic impacts of improved maize production technologies in Ethiopia: Evidence from Panel data. *Journal of Agricultural Economics* 69: 76–95.
Kassie, M., H. Teklewold, M. Jaleta, P. Marenya, and O. Erenstein. 2015. Understanding the adoption of a portfolio of sustainable intensification practices in eastern and Southern Africa. *Land Use Policy* 42: 400–11.
Khonje, M., J. Manda, A.D. Alene, and M. Kassie. 2015. Analysis of adoption and Impacts of Improved maize varieties in eastern Zambia. *World Development* 66, no. 695: 706.
Khonje, M.G., J. Manda, P. Mkandawire, A.H. Tufa, and A.D. Alene. 2018. Adoption and welfare impacts of multiple agricultural technologies: evidence from eastern Zambia. *Agricultural Economics (United Kingdom)* 49: 599–609.
Kiwanuka-Lubinda, R.N., J.N. Ng'ombe, and C. Machethe. 2021. Impacts of interlocked contractual arrangements on dairy farmers' welfare in Zambia: a robust Bayesian instrumental variable analysis. *Agrekon* 60: 10–30.
Lee, N., and C. Thierfelder. 2017. Weed control under conservation agriculture in dryland smallholder farming systems of Southern Africa. *A Review. Agronomy for Sustainable Development* 37: 1–25.
Linden, A., S.D. Uysal, A. Ryan, and J.L. Adams. 2016. Estimating causal effects for multivalued treatments: a comparison of approaches. *Statistics in Medicine* 35: 534–52.
Liverpool-Tasie, L.S.O. 2017. Is fertiliser use inconsistent with expected profit maximization in sub-Saharan Africa? "Evidence from Nigeria". *Journal of Agricultural Economics* 68: 22–44.
Lokshin, M., and E. Glinskaya. 2009. The effect of male migration on employment patterns of women in Nepal. *World Bank Economic Review* 23: 481–507.

Lu, W., K.N. Addai, and J.N. Ng'ombe. 2021. Impact of improved rice varieties on household food security in Northern Ghana: A doubly robust analysis. *Journal of International Development* 33: 342–59.
Manda, J., A.D. Alene, A.H. Tufa, T. Abdoulaye, A.Y. Kamara, O. Olufajo, O. Boukar, and V.M. Manyong. 2020. Adoption and ex-post impacts of improved cowpea varieties on productivity and net returns in Nigeria. *Journal of Agricultural Economics* 71: 165–83.
Manda, J., A.D. Alene, A.H. Tufa, T. Abdoulaye, T. Wossen, D. Chikoye, and V. Manyong. 2019. The poverty impacts of improved cowpea varieties in Nigeria: A counterfactual analysis. *World Development* 122: 261–71.
Manda, J., C. Azzarri, S. Feleke, B. Kotu, L. Claessens, and M. Bekunda. 2021. Welfare impacts of smallholder farmers' participation in multiple output markets: Empirical evidence from Tanzania. *PloS one* 16: e0250848.
Mansur, E.T., R. Mendelsohn, and W. Morrison. 2008. Climate change adaptation: A study of fuel choice and consumption in the US energy sector. *Journal of Environmental Economics and Management* 55: 175–93.
McFadden, D. (1973). Conditional Logit Analysis of Qualitative Choice Be. In: Zarembka, P., Ed., Frontiers in Econometrics, Academic Press, New York, 105–142.
Mutenje, M., H. Kankwamba, J. Mangisonib, and M. Kassie. 2016. Agricultural innovations and food security in Malawi: Gender dynamics, institutions and market implications. *Technological Forecasting and Social Change* 103: 240–8.
Mzyece, A., and J.N. Ng'ombe. 2020. Does crop diversification involve a trade-off between technical efficiency and income stability for rural farmers? evidence from Zambia. *Agronomy* 10: 1–6.
Ng'ombe, J.N., T.H. Kalinda, and G. Tembo. 2017. Does adoption of conservation farming practices result in increased crop revenue? *Evidence from Zambia. Agrekon* 56: 205–21.
Ng'ombe, J.N., T.H. Kalinda, G. Tembo, and E. Kuntashula. 2014. Econometric analysis of the factors that affect adoption of conservation farming practices by smallholder farmers in Zambia. *Journal of Sustainable Development* 7: 124–38.
Nguyen-Van, P., C. Poiraud, and N. To-The. 2017. Modeling farmers' decisions on tea varieties in Vietnam: A multinomial logit analysis. *Agricultural Economics (United Kingdom)* 48: 291–9.
Ojo, T.O., L.J.S. Baiyegunhi, A.A. Adetoro, and A.A. Ogundeji. 2021. Adoption of soil and water conservation technology and its effect on the productivity of smallholder rice farmers in southwest Nigeria. *Heliyon* 7: e06433–e06433.
Pingali, P.L. 2014. Green revolution: Impacts, limits, and the path ahead. 89–106.
Popp, J., K. Pető, and J. Nagy. 2013. Pesticide productivity and food security. A review. *Agronomy for Sustainable Development* 33: 243–55.
Rodrik, D. 2018. An African growth miracle? *Journal of African Economies* 27: 10–27.
Sheahan, M., and C.B. Barrett. 2017. Ten striking facts about agricultural input use in Sub-Saharan Africa. *Food Policy* 67: 12–25.
Somda, J., A.J. Nianogo, S. Nassa, and S. Sanou. 2002. Soil fertility management and socio-economic factors in crop-livestock systems in Burkina Faso: A case study of composting technology. *Ecological Economics* 43: 175–83.
Taylor, J. 2020. Grain and feed annual. 1–21.
Teklewold, H., M. Kassie, B. Shiferaw, and G. Köhlin. 2013. Cropping system diversification, conservation tillage and modern seed adoption in Ethiopia: Impacts on household income, agrochemical use and demand for labor. *Ecological Economics* 93: 85–93.
Villano, R., B. Bravo-Ureta, D. Solís, and E. Fleming. 2015. Modern rice technologies and productivity in the Philippines: Disentangling technology from managerial gaps. *Journal of Agricultural Economics* 66: 129–54.
Wainaina, P., S. Tongruksawattana, and M. Qaim. 2016. Tradeoffs and complementarities in the adoption of improved seeds, fertilizer, and natural resource management technologies in Kenya. *Agricultural Economics (United Kingdom)* 47: 351–62.
Wainaina, P., S. Tongruksawattana, and M. Qaim. 2018. Synergies between different types of agricultural technologies in the Kenyan small farm sector. *Journal of Development Studies* 54: 1974–90.
Wordofa, M.G., J.Y. Hassen, G.S. Endris, C.S. Aweke, D.K. Moges, and D.T. Rorisa. 2021. Adoption of improved agricultural technology and its impact on household income: A propensity score matching estimation in eastern Ethiopia. *Agriculture & Food Security* 10: 1–12.
Wossen, T., A. Alene, T. Abdoulaye, S. Feleke, and V. Manyong. 2019a. Agricultural technology adoption and household welfare: Measurement and evidence. *Food Policy* 87: 101742–101742.
Wossen, T., A. Alene, T. Abdoulaye, S. Feleke, I.Y. Rabbi, and V. Manyong. 2019b. Poverty reduction effects of agricultural technology adoption: The case of improved cassava varieties in Nigeria. *Journal of Agricultural Economics* 70: 392–407.
Wu, J., and B.A. Babcock. 2006. The choice of tillage, rotation, and soil testing practices: Economic and environmental implications. *American Journal of Agricultural Economics* 80: 494–511.
Yaro, J.A., and J. Hesselberg. 2010. The contours of poverty in Northern Ghana: Policy implications for combating food insecurity. *Research Review of the Institute of African Studies* 26: 81–112.
Yigezu, Y.A., A. Mugera, T. El-Shater, A. Aw-Hassan, C. Piggin, A. Haddad, Y. Khalil, and S. Loss. 2018. Enhancing adoption of agricultural technologies requiring high initial investment among smallholders. *Technological Forecasting and Social Change* 134: 199–206.
Zhou, X., and Y. Xie. 2014. Propensity score–based methods versus MTE-based methods in causal inference: Identification, estimation, and application. *Sociological Methods & Research* 45: 3–40.