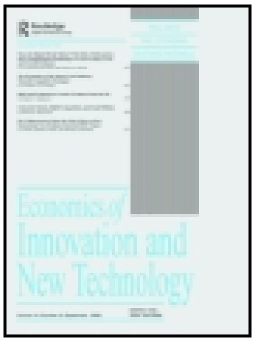

Routledge
Taylor & Francis Group

Economics of Innovation and New Technology

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/gein20

Beyond productivity, does the adoption of agricultural technologies improve food consumption and reduce poverty? Empirical evidence from Benin

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ECONOMICS OF INNOVATION AND NEW TECHNOLOGY
https://doi.org/10.1080/10438599.2022.2144846

RESEARCH ARTICLE

Beyond productivity, does the adoption of agricultural technologies improve food consumption and reduce poverty? Empirical evidence from Benin

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ABSTRACT

Beyond productivity, does the adoption of agricultural technologies improve food consumption and reduce poverty? To provide answers to this, the paper used data from the household survey on the Comprehensive Food Security and Vulnerability Analysis (CFSVA) carried out in 2017 in Benin. Five agricultural technologies were considered in this study. First, an extended ordered probit model was estimated to analyze the impact of technology choice sets on food consumption groups (poor, limit and acceptable). Second, an extended probit model is employed to assess the impact on poverty status. The results show that the adoption of multiple technologies increases food consumption and reduces poverty among agricultural households in Benin. Combinations of technologies that enhance both food consumption and poverty status are irrigation and herbicide, irrigation and chemical fertilizers and improved seed and chemical fertilizers. Therefore, policy interventions should help farming households gain access to these improved technologies to improve food security and reduce poverty.

ARTICLE HISTORY
Received 16 August 2022
Accepted 1 November 2022

KEYWORDS
Agricultural technologies; extended regression models; food consumption; poverty; Benin

JEL CLASSIFICATION
I32; Q12; Q16

1. Introduction

Food security exists when all human beings have, at all times, physical and economic access to sufficient, safe and nutritious food to meet their energy needs and food preferences for leading healthy and active lives. Poverty designates the situation of a person or a group of people who are unable to access sufficient food, drinking water, clothing, housing and heating of the latter when the place of life requires it. These two phenomena are real in Benin and particularly in rural areas where the majority of the population depend on agricultural activities. For example, according to the Word Food Programme (WFP 2017) report, 47.5% of the Benin population is food secure and 42.9% live in borderline food security conditions and, therefore, are at risk of food insecurity. Around 9.6% are food insecure, i.e. 1.09 million people, including 0.7% in severe food insecurity (i.e. 80,000 people). Rural households are more affected by food insecurity (13%) than urban households (7%). The analysis of household expenditure indicates that 38.5% of individuals live below the poverty line (National Institute of Statistics and Economic Analysis, INSAE, 2020). This overall level hides disparities according to the place of residence. Indeed, the incidence of monetary poverty in urban areas is estimated at 31.4% against 44.2% in rural areas. To create balance and improve social conditions within communities and especially rural households, agricultural productivity must be increased. Abate et al. 2018; Nonvide 2017, 2019; Hailu and Mezegebo 2021 have shown that increasing agricultural productivity necessarily involves the adoption of agricultural technologies, in particular

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irrigation, chemical and organic fertilizers, improved seeds, herbicides, etc. However, technology adoption alone is not a sufficient condition. The farmer can use the improved technology on part or all of his field, therefore, the extent of technology adoption is also important for improving production.

To release the potential of agricultural technologies, farmers must adopt them. Statistics in Benin show that only 30.2% of farmers used agricultural inputs, including improved seeds, herbicides, organic fertilizers, chemical fertilizers and insecticides (World Food Programmme (WFP) 2017). Among them, 52.6% applied chemical fertilizers, 21.7% used organic fertilizers (manure), 40.9% used herbicides, 26% used insecticides and only 7.7% of farmers used improved seeds. The use of agricultural technologies in Benin remains low. However, the adoption of agricultural technologies contributes not only to increasing yield but also to improving farmers' food security and poverty status (Mendola 2007; Nonvide 2017; Houeninvo, Quenum, and Nonvide 2020).

Empirically, several studies show the benefits of adopting agricultural technologies. According to Alia et al. (2018), Nerica adoption increases household expenditure among rice farmers in Benin. In Eastern Zambia, Manda et al. (2018) found a positive effect of improved maize varieties' adoption on farm household food security. Lu, Addai, and Ng'ombe (2021) in Ghana showed positive effects of the adoption of improved rice varieties on household food security. In Mexico, Becerril and Abdulai (2010) showed that the adoption of improved maize increases household per capita expenditure by an average of 136–173 Mexican pesos while reducing their probability of falling into poverty by 19–31%. In Nigeria, Wossen et al. (2018) found that the adoption of improved cassava varieties has led to a 4.6 percentage point reduction in poverty. In eastern India, the adoption of modern varieties (MVs) of rice has a positive impact on poverty (Bannor et al. 2020). In Ethiopia, the adoption of farm technologies increases consumption expenditure significantly and the likelihood of a household remaining poor decreases with the adoption of different complementary technologies (Biru, Zeller, and Loos 2020). These results were also confirmed by Belay and Mengiste (2021), Shita, Kumar, and Singh (2021) and Zegeye, Fikire, and Assefa (2022) who found that the adoption of agricultural technologies has a significant impact on increasing consumption expenditure while also reducing poverty among farmers.

From past studies, we observed that the adoption of agricultural technologies has a positive impact on food security and poverty. However, many of these studies are limited. For instance, some studies (Mendola 2007; Becerril and Abdulai 2010; Asfaw et al. 2012a, 2012b; Bezu et al. 2014; Kassie, Jaleta, and Mattei 2014; Alia et al. 2018; Wossen et al. 2018; Ayenew, Tayech Lakew, and Kristos 2020; Shita, Kumar, and Singh 2021) focused on the impact of a single technology. By doing this, they miss considering the multiplicity of technologies. Moreover, among the few studies (Gebeyehu 2016; Khonje et al. 2018; Biru, Zeller, and Loos 2020; Zegeye, Fikire, and Assefa 2022) that consider multiple agricultural technologies, the complementary role and the possible combination of the technologies are excluded, except a study by Khonje et al. (2018) and Biru, Zeller, and Loos (2020). Zegeye, Fikire, and Assefa (2022) considered the state of adoption as if a farm household uses at least one of the following technologies: Inorganic fertilizer, Organic Fertilizer and herbicide. Their study neglected the fact that farmers who adopted one technology might be less impacted compared to those who adopted two or three technologies. In this line, Khonje et al. (2018) and Biru, Zeller, and Loos (2020) found that the greatest impact is achieved when farmers combined multiple complementary technologies.

This study contributes to filling these gaps by assessing the impact of the adoption of agricultural technologies on food consumption and poverty. Because any one technology alone may not be sufficiently important to have the greatest impact (Stoneman and Kwon, 1994, 1996), the paper focuses on multiple agricultural technologies, namely, chemical fertilizers, organic fertilizers, herbicides, improved seeds and irrigation. The complementarity of technologies is controlled by including in the analysis the possible combinations of these technologies. In all, the adoption of the five technologies and their combinations involves 32 possible technology choice sets (including an 'empty' set for non-adoption). In terms of methodology, the study provides rigorous estimate of the impact of agricultural technologies adoption on food consumption and poverty. In fact, the main problem encountered in an impact evaluation is selection bias and endogeneity. To control for these, an extended regression model (ERMs) is estimated. The ERM is a specific class of models that address many complications including sample selection, endogenous covariates, nonrandom treatment assignment and within-panel correlation that arise frequently in data (StataCorp. 2021). Another advantage is that the ERM allows us to derive the average treatment effects. In terms of policy, the results generated in this study would be useful in boosting the agricultural sector as they provide feedback to research on agricultural technology development and serve as evidence for policy formulation on the performance of technologies under real conditions in farmers' fields. A better understanding of the impact will help address the policy failures encountered so far with the adoption of the technology in developing countries and particularly in Benin.

The rest of the paper is organized as follows. Section 2 presents the literature review. Section 3 describes the methodology, followed by the results and discussion in Section 4 and the final section presents the conclusion.

2. Literature review

Theoretically, the adoption of farm technology increases agricultural yield and improves welfare through the reduction of poverty. In fact, the adoption of agricultural technology affects food consumption and poverty in different ways: directly and indirectly (de Janvry and Sadoulet 2002). Directly, the adoption of farm inputs increased the productivity of adopters. As production increases, the home-consumed food may increase along with marketable surplus. Therefore, income also would increase. As income increases, farmers may be able to diversify their food consumption. Indirectly, increased production leads to lower food prices, increased food consumption, job creation and poverty reduction (de Janvry and Sadoulet 2002; Gebeyehu 2016; Biru, Zeller, and Loos 2020).

Assessing the impact of technology adoption faces two major problems: selection bias and the endogenous nature of the adoption variable. Selection bias arises because technology adopters are not a random sample of the population. The use of technology is self-selection. Moreover, those who are better off maybe those who have adopted the technology. In this context, the major question is how to be sure that the difference between program participants and non-participants is caused by participation. A large literature in economics deals with these problems. Randomized control trial is the best approach that provides information on the counterfactual situation and addresses the causal inference problem (Mendola 2007). In the majority of the studies, this is not the case as the baseline data are not available, and this missing data problem leads researchers to use other different approaches. The estimations techniques commonly used include the Heckman selectivity model (Tesfaye et al. 2008; Bacha et al. 2011; Nonvide 2017), the propensity scores matching (PSM) methods (Mendola 2007; Asfaw et al. 2012a; Shita, Kumar, and Singh 2021), the instrumental variable (IV) methods (Bezu et al. 2014; Verkaart et al. 2017; Houeninvo, Quenum, and Nonvide 2020), the endogenous switching regression (ESR) models (Di Falco, Veronesi, and Yesuf 2011; Asfaw et al. 2012a; Nonvide 2019; Zegeye, Fikire, and Assefa 2022) and the extended regressions models (Mounirou and Lokonon 2022). All these methods are complementary and rely on assumptions. For instance, Jalan and Ravallion (2003) argue that the assumption of selection on observables in the PSM approach is no more restrictive than eliminating problems of weak instruments with Heckman and IV models. One limitation of the PSM is that it assumes selection based on observable variables. In other words, unobservable factors that can affect both treatment and outcome are not directly controlled, while the presence of these unobserved variables in the propensity score estimation can create mismatching and biased estimators (Asfaw et al. 2012a). The endogenous switching regression model addresses the weakness in using PSM as it assumes selection on both observable and unobservable factors. The extended regression models (ERMs) are a specific class of models that controlled for many complications that arise frequently in data, namely, sample selection, endogenous covariates, nonrandom treatment assignment and within-panel correlation (StataCorp. 2021).

Various studies analyzed the impact of agricultural technology adoption in Benin. For instance, using instrumental variable (IV) and quantile treatment effect methods, Alia et al. (2018) found that Nerica adoption increases households' expenditure across the entire distribution of income. The impact on farmers located in the upper half of the income distribution is the largest; farmers at the bottom of the income distribution also experienced a large proportional increase in welfare. Houeninvo, Quenum, and Nonvide (2020) using an IV technique found a positive impact of the adoption of improved maize varieties on yield, income and poverty reduction. While they found no heterogeneous impacts for poor and non-poor farmers, their study revealed that the adoption of improved maize seeds favors small landholding farmers. Employing an ordered probit model with sample selection, Nonvide (2018) has shown that the adoption of irrigation has the potential to reduce food insecurity among rice farmers in Benin. Furthermore, Nonvide (2022), based on the estimation of a two-stage instrumental variable probit model, indicates that the use of irrigation contributes to reducing the likelihood of being poor.

Outside Benin, other studies also investigated the impact of agricultural technology adoption on food security and poverty. Among these studies, Mendola (2007) employing a p-score matching analysis, found a positive impact of agricultural technology adoption on farm household well-being in rural Bangladesh. In Mexico, results from propensity score matching estimates indicated a positive impact of improved maize seed on household welfare and poverty reduction (Becerril and Abdulai 2010). Bezu et al. (2014) using a control function approach and an instrumental variable (IV) method found a positive impact of improved maize varieties adoption on household income, assets and maize consumption in Malawi. Using an instrumental variable regression approach, Wossen et al. (2018) suggested that improved cassava variety adoption has led to a reduction in poverty in Nigeria. In Tanzania, Asfaw et al. (2012a) using a propensity score matching and an endogenous switching regression found that the adoption of improved pigeon pea significantly increases consumption expenditure and reduces poverty. Shita, Kumar, and Singh (2021) analyzed the poverty effect of fertilizer adoption in Northern Western Ethiopia based on the propensity score matching technique and dose–response function. They found that fertilizer adoption significantly increases household per-adult consumption expenditure and reduces the incidence of poverty. Zegeye, Fikire, and Assefa (2022) employing the ESR revealed that the adoption of agricultural technology including Inorganic fertilizer, Organic Fertilizer and herbicide, significantly increases household food consumption expenditure per adult equivalent in Ethiopia. These results confirm previous findings by Biru, Zeller, and Loos (2020) in Ethiopia, moreover, the study highlighted the impact of the combinations of agricultural technologies. Indeed farming households have the possibility for technology choice set. Biru, Zeller, and Loos (2020) included multiple agricultural technologies such as chemical fertilizer, pesticides and improved seed, terraces and contour plowing and their possible combinations. They found that the adoption of farming technologies increases consumption expenditure significantly, and the likelihood of households being poor decreased. Their results also revealed that the greatest impact is reached when farmers combined multiple complementary technologies.

While employing different estimations techniques, the above studies suggested that the adoption of agricultural technology has the potential to contribute to the improvement of food security and reduction of poverty among farm households. This suggests that poverty reduction programs can be effective among rural households through improvement in access to agricultural technology. However, the gap identified in the literature is the fact that most of these previous studies focused on a single agricultural technology, thus, excluding the possible combinations and complementarity of the technologies. In this line, previous studies (Stoneman and Kwon 1996; Battisti and Stoneman 2010, 2021) argued that the undertaking of one technology may raise the marginal pay-off of undertaking the other.

3. Empirical approach

In this study, the analysis is based on a non-separable model of farm households and agricultural households' resource allocation is determined simultaneously to maximize utility over the consumption of goods and leisure (de Janvry, Fafchamps, and Sadoulet 1991; Verkaart et al. 2017; Biru, Zeller, and Loos 2020; Houeninvo, Quenum, and Nonvide 2020). Like those of any developing country, agricultural households in Benin are simultaneously engaged in both food production and consumption. They produce goods for consumption or sale and face various constraints including imperfect input and credit markets, high transaction costs and unemployment. Furthermore, the households' livelihood strategies are affected by economic shocks such as pests and diseases and agro-climatic conditions which influence their productivity. Against this backdrop, the introduction of agricultural technologies meets farmers' expectations to increase productivity and improve their living conditions.

3.1. The models

The outcome variables (food consumption and poverty status) are considered as a linear function of observed farm and households characteristics, along with the technology adoption variables. The general model estimated is presented as follows:

$$Y_i = \beta X_i + \delta A_i + \gamma R_i + \varepsilon_i \tag{1}$$

where Y_i are the outcome variables (food consumption and poverty status). X_i represents the vector of farm and household characteristics; R_i represents region-level dummies; A_i is the vector of technologies adopted; β, δ, γ denote the vectors of coefficients and ε_i is the error term. The five technologies considered include irrigation, improved seed, herbicide, chemical fertilizers and organic fertilizers. These technologies and their combinations involve 32 possible technologies choice sets including an 'empty' set for non-adoption. Then, we specified 32 equations for each technology choice set. However, some technology choice sets were dropped because of insufficient observations which lead to iteration and non-concavity problems. Finally, the number of technology choice sets is reduced to 17 including the 'empty set' for non-adoption.

The two outcome variables considered in this study are food consumption score and poverty status. Indeed, the food consumption score (FCS) is an indicator based on the frequency of food consumption and diversity over a reference period of the last seven days preceding the study. It is an acceptable proxy indicator for measuring caloric intake and diet quality at the household level, thus indicating household food security status. In addition, it is a composite score, based on dietary diversity; the frequency of consumption and the relative nutritional importance of different food groups. It is mainly used by the WFP.

The FCS is determined by the following formula:

$$SCA = \sum a_i X_i \tag{2}$$

where a_i is the weight of each food group and Xi the frequency of food consumption. An FCS < 21 corresponds to poor food consumption, 21 < FCS < 35 to borderline food consumption and an FCS > 35 to acceptable food consumption (WFP, 2017).

Consumption expenditures are used in Benin to analyze poverty. This remains a better proxy of poverty as it is subject to less variation than income. Also, income is difficult to measure in developing countries such as Benin where it is largely derived from agriculture or self-employment (Deaton and Zaidi 2002; Nonvide 2022). To identify the poor and the non-poor, a per capita consumption expenditure and the national poverty line, which is CFA 246 542 per year (about 20 545 per month) per person (INSAE 2020) are used. Household *i* is categorized as poor when his per capita consumption expenditure is less than the poverty line. Otherwise, the household is classified as a non-poor household.

Separate regressions were estimated for each indicator (food consumption and poverty status).

(a) Ordered probit model for food consumption groups

As food consumption can be conceptualized as a categorical variable (comprising poor food consumption, borderline food consumption and acceptable food consumption) composed of three categories, and assuming a normal distribution function form, an ordered probit model can be applied. This is employed to take advantage of the ordinal nature of the food consumption categories (Nata, Mjelde, and Boadu 2014; Nonvide 2018). For instance, a farmer in a borderline food consumption group is worse off than a farmer in the acceptable food consumption category, but he is better off than a farmer in a poor food consumption category. Therefore, grouping the different food consumption groups into a single food consumption category can be misleading because it fails to distinguish between serious and less serious conditions of food consumption. The ordered probit model is an extension of the simple probit model by adding multiple cutoff points. For the three food consumption categories model, the observed aspect of food consumption can be written as follows:

$$\begin{cases} \textit{poor food consumption category} & \text{if} \quad \beta X_i + \delta A_i + \gamma R_i < \mu_1 \\ \textit{borderline food consumption category} & \text{if} \quad \mu_1 < \beta X_i + \delta A_i + \gamma R_i < \mu_2 \\ \textit{acceptable food consumption category} & \text{if} \quad \beta X_i + \delta A_i + \gamma R_i > \mu_2 \end{cases} \tag{3}$$

where μ_1 and μ_2 are the cutoff points. With the three categories of the food consumption model, two cutoff points are estimated.

(b) Probit model for the poverty status

For the poverty status, because this is a binary variable indicating whether a farmer is poor or non-poor, a simple probit model can be applied. The model is specified as follows:

$$P_i = \beta X_i + \delta A_i + \gamma R_i + \varepsilon_i \tag{4}$$

where P_i is the binary response variable with a value of 1 if a farmer is poor and 0 otherwise.

The two models include the same independent variables. For the food consumption categories model, 12 valid technology choice sets are used, while for the poverty status model, 16 valid technology choice sets are used.

3.2. Endogeneity issues and estimation techniques

Equation (1) may suffer from two problems. Firstly, self-selection usually occurs in the technologies' adoption process given that households decide themselves to adopt or not a particular technology. Also, because of some unobservable characteristics (skill, motivation, risk preference, etc.), some households are more likely to adopt technologies than others. Secondly, the treatment variable (adoption of technologies) and outcome variables in Equation (1) seem to be bi-causal in the sense that the adoption of technologies affects food consumption and poverty, while households who adopt the technologies may be the ones who actually are more food secure and non-poor. This reverse causality creates the endogeneity problem.

The main question now is how can we be sure that the better food security and poverty status of technology adopters compared to non-adopters is caused by technology adoption or not? In a counterfactual framework, the indicator of interest is the average treatment effect (ATE) which is defined by Rosembaum and Rubin (1983) as follows:

$$ATE = E\,(Y_i^1 - Y_i^0) \tag{3}$$

where Y_i^1 is the outcome in the case of technology adoption and Y_i^0 in the case of non-adoption.

The main problem in estimating the causal effect (2) is that only Y_i^1 or Y_i^0 is observed and not for both households. Following Mendola (2007) the following is observed:

$$Y_i = A_i Y_i^1 + (1 - A_i) Y_i^0,\ A = 0,\ 1 \tag{4}$$

Then the expression of the ATE can be rewritten as follows:

$$ATE = P*(E\,(Y^1/A = 1)\; - \;E\,(Y^0/A = 1))\; + (1 - P)*(E\,(Y^1/A = 0)\; - \;E\,(Y^0/A = 0)) \qquad (5)$$

where P is the probability of observing households with $A = 1$ in the sample. Equation (5) assumes that the impact of agricultural technology adoption on food consumption and poverty status for the entire sample is the weighted average of the impact in the two groups of households, the treated in the first term, and the controls in the second term; each group weighted by its relative frequency. However, it is still not possible to estimate the unobserved counterfactuals $E\,(Y^1/A = 0)$ and $E\,(Y^0/A = 1)$. This is the fundamental problem of causal inference (Heckman et al. 1998; Mendola 2007).

Normally, experimental data are the best way to provide us with information on the counterfactual situation that would solve the problem of causal inference. In the absence of that, the study employed the Extended regression models (ERMs), which are a specific class of models that address many complications that arise frequently in data, namely, sample selection, endogenous covariates, nonrandom treatment assignment and within-panel correlation (StataCorp. 2021). The ERMs permit us to make valid inferences as if these complications did not occur in the dataset. Another advantage is that the ERMs allow us to derive the average treatment effects. ERMs require us to satisfy the exclusion restriction assumption, meaning that variables that are strongly correlated to the treatment while not correlated to the outcomes variables should be excluded from the outcome equation. Therefore, the vector of explanatory variables X contains an exclusion restriction variable, which is membership in a community cooperative. This instrument is valid if it affects the treatment equation (probability of technology adoption) but not the outcomes (Di Falco, Veronesi, and Yesuf 2011; Mounirou and Lokonon 2022). Indeed, being a member of a community cooperative can increase the likelihood of adopting agricultural technologies but does not directly affect the food consumption and poverty status of the households.

The extended regression model commands fit linear regressions, interval regressions, probit regressions and ordered probit regressions. Stata command 'eoprobit' is used for the extended ordered probit estimation, while the command 'eprobit' is used for the estimation of the extended probit model. STATA version 15 is used for the estimations.

4. Data

The data used come from the household survey on the Comprehensive Food Security and Vulnerability Analysis (CFSVA) carried out in 2017 in Benin by the National Institute of Statistics, the Ministry of Agriculture, Livestock and Fisheries, the World Food Program (WFP) and the Ministry of Health. The household survey covered a sample of 15,000 households, representative at the national, departmental and communal levels and by place of residence. This sample was drawn using a two-stage sampling technique, with a margin error of 5%. In the first stage, 750 clusters were drawn from the 920 clusters surveyed during the 2015 Living Standards Survey, then at the second stage, 20 households were systematically drawn from each cluster. The sample was drawn by urban/rural stratum at the level of each municipality. A total of 148 strata were thus defined. The sample households were distributed in each department in proportion to their size in several households. Thus, 8320 households were surveyed in rural areas against 6680 in urban areas. The survey took place from July 20 to August 20, 2017, in Benin. The analysis in this study focuses only on 6502 agricultural households.

5. Results and discussion

5.1. Descriptive statistics

Table 1 shows the prevalence of food consumption categories and poverty status among the surveyed agricultural household. The analysis shows that 1.89%, 17.64% and 80.47% of the households have poor, limited and acceptable food consumption, respectively. 55.57% of households are poor.

The description of the explanatory variables and the summary statistics are presented in Table 2.

The average age of household heads is 46 years, and the majority of the household head are male and are married to an average of 4 household members. The majority of household heads are uneducated as only 18% have primary education, 9% have secondary education and 1% have higher education. The average farm size is 3.4 ha and about 55% of households own livestock. Only 30% of households have access to credit and 51% to media (radio or TV). A few proportions (4%) of households have a member who migrated during the 12 months before the survey. Regarding the adoption of technologies only 6% of the surveyed households used irrigation, 8% used improved seeds and 22% used organic fertilizers. A relatively higher proportion of households used herbicides (45%) and chemical fertilizers (56%). In terms of intensity, it observed that farmers adopted on average one technology. About 6% of households head belong to a community cooperative. Regarding the location, about 51% of agricultural households are in the northern region against 15% in the central region and 33% in the southern region.

5.2. Estimates of the extended ordered probit model: impact of technologies' adoption on food consumption groups

Using food consumption groups as a dependent variable, an extended ordered probit model is estimated to assess the impact of agricultural technologies on food consumption. The results of the 12 valid technology choice sets are presented in Table 3. The significance of the Wald test in all the equations estimated indicates that our models have a good fit with the explanatory variables. The estimated cut-off points satisfy the conditions that $\mu_1 < \mu_{2,}$ implying that the three categories of food consumption differ, and should be included in the model. The majority of correlation coefficients between treatment and outcome equations are significant, supporting the presence of both observed and unobserved factors affecting both technology choice sets and food consumption. Results from the marginal effects of the different food consumption groups are not presented since the main focus in this analysis is the estimation of the average treatment effect (ATE), as reported in Table 4 based on the three categories of food consumption.

However, from the estimated coefficients presented in Table 3, it is observed regional disparities in terms of food consumption. Indeed, compared to the northern region, households in other regions (central and southern) are better off in terms of food consumption. Farm size, ownership of livestock and access to media appeared to positively affect households' food consumption. Surprisingly, access to credit negatively affects the food consumption of households, suggesting that households with access to credit are less likely to be in the acceptable food consumption group. This result highlights the fact that access to credit is limited in developing countries, especially in Benin. Indeed, from the summary statistic (Table 2) it is observed that only 30% of households have access to credit. Moreover, only 33.64% of households have reported using the credit contracted for inputs purchases and 15.24% used it for food purchases. The rest used (more than

Table 1. Food consumption groups and poverty status of the households.

Variables	Frequencies
Poor food consumption	1.89
Limit food consumption	17.64
Acceptable food consumption	80.47
Poor households	55.57
Poverty gap	0.28
Poverty severity	0.18

Source: Calculation based on the 2017 CFSVA data.

Table 2. Summary statistics of explanatory variables.

Variables	Mean	Standard deviation	Minimum	Maximum
Age (in years)	46.46	14.11	16	100
Married (yes = 1)	0.90	0.29	0	1
Male (yes = 1)	0.89	0.31	0	1
Household size (number)	3.51	2.66	0	50
Primary education (yes = 1)	0.18	0.38	0	1
Secondary education (yes = 1)	0.09	0.29	0	1
University (yes = 1)	0.010	0.10	0	1
Land size (in ha)	3.43	1.82	1	6
Ownership of livestock (yes = 1)	0.55	0.49	0	1
Credit access (yes = 1)	0.30	0.45	0	1
Access to media (1 if radio or TV)	0.51	0.49	0	1
Migration (yes = 1 if at least one household member migrated in the last 12 months)	0.04	0.21	0	1
Use of irrigation (yes = 1)	0.06	0.24	0	1
Use of improved seed (yes = 1)	0.08	0.27	0	1
Use of herbicide (yes = 1)	0.45	0.49	0	1
Use of chemical fertilizers (yes = 1)	0.56	0.49	0	1
Use of organic fertilizers (yes = 1)	0.22	0.41	0	1
Number of technology adopted (number)	1.39	1.09	0	5
Being a member of a community cooperative (yes = 1)	0.06	0.24	0	1
Northern region (yes = 1)	0.51	0.49	0	1
Central region (yes = 1)	0.15	0.36	0	1
Southern region (yes = 1)	0.33	0.47	0	1

Source: Calculation based on the 2017 CFSVA data.

50% of households) the credit for other expenses including healthcare, school fees payment, house rent and weeding.

The average treatment effect (ATE) reported in Table 4 reveals that among the technologies considered in this study, the adoption of irrigation and improved seed significantly contribute to improving food consumption. Compared to non-adopters, the adoption of irrigation decreases the probability of being poor or in limited food groups while increasing the probability of being in an acceptable food consumption group by 20.4%. Similarly, for the improved seed users, the probability is higher by 19.4%. Furthermore, the combination of irrigation and herbicide, irrigation and chemical fertilizers and improved seed and chemical fertilizers increase the probability of being in the acceptable food consumption group by 19.5%, 20.1% and 21.8% respectively. The combination of herbicide with chemical fertilizers only increases the probability of being in a limited food consumption group. However, the combination of herbicide with organic fertilizers, chemical fertilizers with organic fertilizers and herbicide with chemical fertilizers and organic fertilizers produces negative impacts. These combinations do not help households to improve their food consumption status. The findings highlight the substitution effects among technologies. For instance, the adoption of chemical fertilizers may substitute the adoption of organic fertilizers (Biru, Zeller, and Loos 2020).

5.3. Estimates of the extended probit model: impact of technologies adoption on poverty status

To analyze the impact of single technologies adoption and their possible combinations on poverty, an extended probit model is estimated. The results of the 16 valid technology choice sets are presented in Table 5. The findings reveal the endogenous nature of the technology adoption given the significance of the correlation between the two equations (treatment and outcome) in all equations estimated. Household size and region dummies variables were significant in all the estimated equations. The sign associated with the household size is positive, suggesting that households with more family members are more likely to be poor. The results also indicate that the impact of technology adoption on poverty status depends on the location. In fact, compared to

Table 3. Impact of agricultural technology choice sets on household food consumption.

Dependent variable: food consumption groups	Irrigation	Improved seed	Herbicide	Organic fertilizers	Chemical fertilizers	Irrigation and herbicide	Irrigation and chemical fertilizers
Age	−0.0398	−0.0120	0.00571	−0.0208	0.00544	−0.0308	−0.0483
	(0.0309)	(0.0228)	(0.0104)	(0.0143)	(0.00920)	(0.0435)	(0.0371)
Age square	0.000439	0.000109	−3.94e−05	0.000196	−4.32e−05	0.000337	0.000551
	(0.000315)	(0.000216)	(9.98e−05)	(0.000134)	(8.82e−05)	(0.000414)	(0.000362)
Sex	0.000968	−0.172	−0.0459	0.118	0.00161	0.0948	0.0134
	(0.218)	(0.233)	(0.0956)	(0.150)	(0.0840)	(0.426)	(0.286)
Education (yes = 1)	−0.0239	0.161	0.0597	−0.0911	0.00116	−0.216	0.0706
	(0.150)	(0.156)	(0.0630)	(0.0899)	(0.0609)	(0.211)	(0.193)
Household size (in number)	−0.0338	−0.0104	−0.0122	−0.0145	−0.0146	0.00579	−0.000752
	(0.0242)	(0.0239)	(0.00993)	(0.0162)	(0.00891)	(0.0360)	(0.0325)
Farm size (in ha)	0.0690*	0.171***	0.158***	0.0410	0.107***	0.125**	0.0930*
	(0.0399)	(0.0480)	(0.0243)	(0.0503)	(0.0233)	(0.0559)	(0.0493)
Credit Access (Yes = 1)	−0.414***	0.00740	−0.0224	0.137	−0.0186	−0.314*	−0.526***
	(0.127)	(0.157)	(0.0624)	(0.109)	(0.0588)	(0.181)	(0.154)
Ownership of livestock	0.134	0.465***	0.136**	0.0155	0.193***	0.103	0.0229
	(0.145)	(0.155)	(0.0557)	(0.0795)	(0.0515)	(0.210)	(0.184)
Access to media (1 if TV or Radio)	0.674***	0.142	0.504***	0.322***	0.483***	0.979***	0.819***
	(0.160)	(0.144)	(0.0532)	(0.116)	(0.0513)	(0.236)	(0.200)
Migration (1 if any household member migrates)	0.140	−0.0418	−0.232**	−0.0269	−0.358***	−0.107	0.153
	(0.270)	(0.291)	(0.112)	(0.169)	(0.105)	(0.349)	(0.349)
Region (reference: Northern region)							
Central region	0.971***	0.689**	0.0855	−0.0556	0.121	1.204**	0.731**
	(0.305)	(0.291)	(0.147)	(0.240)	(0.133)	(0.475)	(0.350)
Southern region	0.565***	1.072***	0.231	−0.00209	0.364***	1.303***	0.802***
	(0.170)	(0.213)	(0.190)	(0.123)	(0.0993)	(0.345)	(0.238)
Correlation (technology*food consumption category)	−0.692***	−0.534**	0.500**	−0.454	0.103	−0.674***	−0.702***
	(0.139)	(0.272)	(0.235)	(0.540)	(0.264)	(0.143)	(0.130)
Wald chi2	223.74***	236.94***	438.35***	180.50***	382.91***	327.18***	247.69***
Observations	6502	6502	6502	6502	6502	6502	6502

Dependent variable: food consumption groups	Improved seed and chemical fertilizers	Herbicide and organic fertilizers	Herbicide and chemical fertilizers	Chemical fertilizers and organic fertilizers	Herbicide and chemical fertilizers and organic fertilizers
Age	0.0199	0.0127	0.00550	−0.0154	0.00668
	(0.0260)	(0.0125)	(0.0114)	(0.0192)	(0.0102)
Age square	−0.000194	−0.000106	−2.71e−05	0.000172	−5.25e−05
	(0.000246)	(0.000116)	(0.000109)	(0.000181)	(9.79e−05)
Sex	0.0649	0.00353	−0.147	−0.0582	−0.0901
	(0.245)	(0.117)	(0.111)	(0.264)	(0.0930)

(*Continued*)

Table 3. Continued.

Dependent variable: food consumption groups	Improved seed and chemical fertilizers	Herbicide and organic fertilizers	Herbicide and chemical fertilizers	Chemical fertilizers and organic fertilizers	Herbicide and chemical fertilizers and organic fertilizers
Education (yes = 1)	0.210	0.0186	0.0626	−0.0583	0.0803
	(0.223)	(0.0901)	(0.0718)	(0.134)	(0.0617)
Household size (in number)	0.0147	−0.0127	−0.00820	−0.0263	−0.00735
	(0.0299)	(0.0118)	(0.0109)	(0.0198)	(0.00940)
Farm size (in ha)	0.0702	0.138***	0.181***	0.0389	0.150***
	(0.0560)	(0.0217)	(0.0253)	(0.107)	(0.0179)
Credit Access (Yes = 1)	−0.393**	−0.168	−0.0633	0.0537	−0.260***
	(0.164)	(0.114)	(0.0663)	(0.253)	(0.0638)
Ownership of livestock	0.467**	−0.0426	0.194***	0.00255	0.0385
	(0.199)	(0.0621)	(0.0649)	(0.108)	(0.0414)
Access to media (1 if TV or Radio)	0.243	0.284**	0.513***	0.336***	0.113*
	(0.163)	(0.120)	(0.0650)	(0.104)	(0.0615)
Migration (1 if any household member migrates)	0.417	−0.162	−0.329***	−0.212	−0.245**
	(0.396)	(0.139)	(0.124)	(0.231)	(0.121)
Region (reference: Northern region)					
Central region	0.694**	−0.518***	0.0623	−0.318	−0.435***
	(0.308)	(0.119)	(0.211)	(0.292)	(0.0946)
Southern region	0.875***	−0.148	0.134	−0.153	−0.0364
	(0.266)	(0.0918)	(0.203)	(0.328)	(0.0792)
Correlation (technology*food consumption category)	−0.722***	0.913***	0.522**	−0.001	0.981***
	(0.134)	(0.114)	(0.247)	(1.084)	(0.012)
Wald chi2	308.81***	495.50***	453.31***	318.73***	500.52***
Observations	6502	6502	6502	6502	6502

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$. Values in parentheses are robust standard errors.

Table 4. ATE of the impact of agricultural technology choice sets food consumption groups.

	Irrigation	Improved seed	Herbicide	Organic fertilizers	Chemical fertilizers	Irrigation and herbicide	Irrigation and chemical fertilizers
Pr (Poor food consumption)	−0.032***	−0.029***	0.047	−0.036	0.002	−0.027***	−0.029***
	(0.007)	(0.010)	(0.053)	(0.038)	(0.019)	(0.004)	(0.005)
Pr (Limit food consumption)	−0.172***	−0.165***	0.135**	−0.168	−0.004	−0.168***	−0.172***
	(0.014)	(0.037)	(0.073)	(0.114)	(0.094)	(0.013)	(0.011)
Pr (Acceptable food consumption)	0.204***	0.194***	−0.183	0.204	0.002	0.195***	0.201***
	(0.020)	(0.047)	(0.126)	(0.153)	(0.114)	(0.017)	(0.015)
Observations	6502	6502	6502	6502	6502	6502	6502

	Improved seed and chemical fertilizers	Herbicide and organic fertilizers	Herbicide and chemical fertilizers	Chemical fertilizers and organic fertilizers	Herbicide and chemical fertilizers and organic fertilizers
Pr (Poor food consumption)	−0.031***	0.570**	0.070	−0.014	0.797***
	(0.006)	(0.266)	(0.082)	(0.044)	(0.041)
Pr (Limit food consumption)	−0.186***	0.054	0.157**	−0.053	−0.086***
	(0.007)	(0.167)	(0.070)	(0.395)	(0.031)
Pr (Acceptable food consumption)	0.218***	−0.624***	−0.228	0.067	−0.710***
	(0.011)	(0.100)	(0.151)	(0.439)	(0.012)
Observations	6502	6502	6502	6502	6502

***$p < 0.01$; **$p < 0.05$.Values in parentheses are robust standard errors.

Table 5. Impact of agricultural technology choice sets on poverty status.

Dependent variable: poverty status, 1 if poor and 0 otherwise	Irrigation	Improved seed	Herbicide	Organic fertilizers	Chemical fertilizers	Irrigation and herbicide	Irrigation and chemical fertilizers	Irrigation and organic fertilizers
Age	−0.00180	0.00149	−0.0244***	−0.0373***	−0.0316***	0.00144	−0.00996	−0.000945
	(0.0230)	(0.0191)	(0.00866)	(0.0144)	(0.00857)	(0.0307)	(0.0272)	(0.0465)
Age square	−2.01e−05	−2.10e−05	0.000204**	0.000340**	0.000260***	−9.73e−05	9.07e−05	7.98e−05
	(0.000230)	(0.000185)	(8.22e−05)	(0.000139)	(8.23e−05)	(0.000297)	(0.000264)	(0.000454)
Sex	−0.256	−0.0570	−0.304***	−0.202*	−0.318***	−0.0891	−0.193	−0.434
	(0.158)	(0.169)	(0.0795)	(0.122)	(0.0742)	(0.264)	(0.200)	(0.411)
Education (yes = 1)	−0.0574	−0.0416	−0.202***	−0.231***	−0.241***	0.0544	−0.0629	0.238
	(0.112)	(0.105)	(0.0545)	(0.0860)	(0.0535)	(0.144)	(0.132)	(0.217)
Household size (in number)	0.205***	0.247***	0.327***	0.418***	0.385***	0.205***	0.222***	0.269***
	(0.0353)	(0.0383)	(0.0216)	(0.0291)	(0.0262)	(0.0508)	(0.0437)	(0.0714)
Farm size (in ha)	−0.0419	−0.114***	−0.0447***	−0.165***	−0.118***	−0.0328	−0.0229	0.104
	(0.0298)	(0.0274)	(0.0173)	(0.0261)	(0.0195)	(0.0384)	(0.0353)	(0.0687)
Credit Access (Yes = 1)	0.0994	−0.159	−0.151***	−0.401***	−0.183***	0.281**	0.0950	−0.110
	(0.0937)	(0.0993)	(0.0525)	(0.0987)	(0.0519)	(0.124)	(0.109)	(0.231)
Ownership of livestock	−0.191*	0.0532	−0.0962**	0.0370	−0.108**	0.0239	−0.0414	−0.563**
	(0.0988)	(0.0878)	(0.0444)	(0.0759)	(0.0436)	(0.141)	(0.117)	(0.255)
Access to media (1 if TV or Radio)	−0.297***	−0.0697	−0.115**	−0.311***	−0.327***	−0.290**	−0.449***	−0.284
	(0.0967)	(0.0865)	(0.0467)	(0.0737)	(0.0471)	(0.138)	(0.125)	(0.224)
Migration (1 if any household member migrates)	−0.129	−0.0652	−0.239**	−0.187	−0.142	−0.170	−0.334	0.389
	(0.188)	(0.190)	(0.109)	(0.167)	(0.105)	(0.224)	(0.225)	(0.396)
Region (reference: Northern region)								
Central region	−0.564***	−0.563***	−0.428***	0.507***	−0.407***	−0.798***	−0.646***	−0.874*
	(0.178)	(0.186)	(0.0753)	(0.150)	(0.0842)	(0.232)	(0.224)	(0.472)
Southern region	−0.464***	−0.837***	−0.705***	−0.481***	−0.567***	−0.957***	−0.482***	−0.258
	(0.124)	(0.122)	(0.0690)	(0.106)	(0.0619)	(0.206)	(0.148)	(0.272)
Correlation (technology*poverty status)	0.876***	0.853***	0.802***	−0.382***	0.688***	0.859***	0.889***	0.817***
	(0.037)	(0.038)	(0.044)	(0.090)	(0.083)	(0.062)	(0.041)	(0.073)
Wald chi2	2212.59***	2370.83***	2871.46***	1319.87***	2266.92***	1894.81***	2001.98***	1563.68***
Observations	6502	6502	6502	6502	6502	6502	6502	6502

Dependent variable: poverty status, 1 if poor and 0 otherwise	Improved seed and herbicide	Improved seed and chemical fertilizers	Improved seed and organic fertilizers	Herbicide and organic fertilizers	Herbicide and chemical fertilizers	Chemical fertilizers and organic fertilizers	Herbicide and chemical fertilizers and organic fertilizers	Improved seed and chemical fertilizers and organic fertilizers
Age	−0.00846	−0.00260	−0.0260	−0.0477**	−0.0232**	−0.0446**	−0.0424**	−0.0361
	(0.0269)	(0.0259)	(0.0336)	(0.0191)	(0.00970)	(0.0177)	(0.0215)	(0.0366)

(*Continued*)

Table 5. Continued.

Dependent variable: poverty status, 1 if poor and 0 otherwise	Improved seed and herbicide	Improved seed and chemical fertilizers	Improved seed and organic fertilizers	Herbicide and organic fertilizers	Herbicide and chemical fertilizers	Chemical fertilizers and organic fertilizers	Herbicide and chemical fertilizers and organic fertilizers	Improved seed and chemical fertilizers and organic fertilizers
Age square	0.000138	5.93e−05	0.000242	0.000430**	0.000202**	0.000384**	0.000369*	0.000362
	(0.000258)	(0.000247)	(0.000325)	(0.000181)	(9.19e−05)	(0.000169)	(0.000202)	(0.000337)
Sex	−0.00546	−0.186	0.783**	−0.204	−0.346***	−0.269*	−0.478**	0.104
	(0.239)	(0.212)	(0.357)	(0.180)	(0.0915)	(0.152)	(0.208)	(0.603)
Education (yes = 1)	−0.246	−0.177	0.109	−0.242**	−0.181***	−0.242**	−0.236*	0.0381
	(0.184)	(0.145)	(0.173)	(0.114)	(0.0614)	(0.109)	(0.133)	(0.225)
Household size (in number)	0.273***	0.234***	0.251***	0.453***	0.335***	0.470***	0.462***	0.232***
	(0.0673)	(0.0510)	(0.0701)	(0.0356)	(0.0245)	(0.0353)	(0.0418)	(0.0803)
Farm size (in ha)	−0.0783	−0.0371	−0.115**	−0.153***	−0.0522***	−0.180***	−0.184***	−0.0520
	(0.0513)	(0.0344)	(0.0493)	(0.0341)	(0.0200)	(0.0349)	(0.0416)	(0.0622)
Credit Access (Yes = 1)	0.110	−0.0178	−0.823***	−0.530***	−0.220***	−0.497***	−0.699***	−0.992***
	(0.142)	(0.128)	(0.257)	(0.153)	(0.0602)	(0.125)	(0.176)	(0.350)
Ownership of livestock	0.0919	−0.102	−0.152	0.0903	−0.0963*	−0.0127	0.170	−0.143
	(0.154)	(0.124)	(0.169)	(0.102)	(0.0501)	(0.0963)	(0.120)	(0.232)
Access to media (1 if TV or Radio)	−0.0904	−0.155	−0.128	−0.268***	−0.149***	−0.279***	−0.252**	−0.181
	(0.132)	(0.112)	(0.143)	(0.0961)	(0.0526)	(0.0939)	(0.113)	(0.182)
Migration (1 if any household member migrates)	0.0232	−0.298	0.247	−0.165	−0.354***	−0.181	−0.204	−0.0454
	(0.233)	(0.239)	(0.273)	(0.245)	(0.126)	(0.210)	(0.260)	(0.330)
Region (reference: Northern region)								
Central region	−0.841***	−0.491**	0.659	0.393**	−0.595***	0.508**	0.385	0.355
	(0.298)	(0.213)	(0.555)	(0.194)	(0.0983)	(0.202)	(0.245)	(0.703)
Southern region	−1.166***	−1.047***	−0.700**	−0.491***	−0.738***	−0.586***	−0.700***	−0.872**
	(0.248)	(0.198)	(0.284)	(0.152)	(0.0771)	(0.140)	(0.178)	(0.388)
Correlation (technology*poverty status)	0.750***	0.831***	0.902***	−0.320***	0.789***	−0.226*	−0.286***	0.889***
	(0.118)	(0.060)	(0.035)	(0.077)	(0.048)	(0.122)	(0.079)	(0.037)
Wald chi2	1623.69***	1926.01***	2060.01***	1261.22***	2692.39***	1232.75***	1230.52***	1806.40***
Observations	6502	6502	6502	6502	6502	6502	6502	6502

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$. Values in parentheses are robust standard errors.

Table 6. ATE of the impact of agricultural technology choice sets on poverty status.

Technology choice sets	Irrigation	Improved seed	Herbicide	Organic fertilizers	Chemical fertilizers	Irrigation and herbicide	Irrigation and chemical fertilizers	Irrigation and organic fertilizers
ATE	−0.472***	−0.468***	−0.443***	0.169***	−0.370***	−0.490***	−0.476***	−0.482***
	(0.018)	(0.019)	(0.021)	(0.045)	(0.038)	(0.021)	(0.021)	(0.031)
Technology choice sets	**Improved seed and herbicide**	**Improved seed and chemical fertilizers**	**Improved seed and organic fertilizers**	**Herbicide and organic fertilizers**	**Herbicide and chemical fertilizers**	**Chemical fertilizers and organic fertilizers**	**Herbicide and chemical fertilizers and organic fertilizers**	**Improved seed and chemical fertilizers and organic fertilizers**
ATE	−0.461***	−0.478***	−0.473***	0.106**	−0.429***	0.085	0.081*	−0.490***
	(0.041)	(0.023)	(0.029)	(0.045)	(0.022)	(0.062)	(0.047)	(0.026)
Observations	6502	6502	6502	6502	6502	6502	6502	6502

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$. Values in parentheses are standard errors.

the northern region, households in central and southern regions are less likely to be poor. This is in line with the general figures in Benin where poverty incidence is high among the northern population. Indeed at least 40% of the population in northern Benin is poor (INSAE 2020). In a majority of equations, coefficients associated with farm size, access to credit and access to media are negative, suggesting that these variables contribute to decreasing poverty.

Table 6 reports the average treatment effect (ATE). Estimates of the ATE indicate that compared to non-adopters, adoption of irrigation, improved seed, herbicide and chemical fertilizers with no other complementary inputs reduces the probability of being poor by 47.2%, 46.8%, 44.3% and 37%, respectively. The highest impact of adoption is observed for the technology combination of improved seed, chemical fertilizers and organic fertilizers and irrigation and herbicide, which reduce the probability of being poor by 49%. This is followed by the combinations of irrigation and organic fertilizers, improved seed and chemical fertilizers and improved seed and organic fertilizers, which reduce the probability of being poor by between 47.3% and 48.2%. However, the combinations of herbicides with organic fertilizers and herbicides with chemical fertilizers and organic fertilizers gave a positive impact, suggesting that these combinations do not help households to escape from poverty.

Overall, the findings show that the adoption of multiple technologies improves the food consumption status while decreasing the probability of being poor. The findings are in line with previous studies (Gebeyehu 2016; Biru, Zeller, and Loos (2020) that show that the greatest impact of agricultural technology adoption is obtained when households combine multiple complementary technologies. Therefore, agricultural households' welfare-improving technologies should involve a package of technologies instead of a single one.

6. Conclusion

This paper assessed the impact of agricultural technology adoption on households' food consumption and poverty status in Benin. Extended regression models are employed. Five technology with their combinations were considered in this study. The results show that the adoption of multiple technologies increases food consumption and reduces poverty among agricultural households in Benin. The combinations of irrigation and herbicide, irrigation and chemical fertilizers and improved seed and chemical fertilizers increase the probability of being in an acceptable food consumption group. Irrigation adoption combined with herbicide, irrigation with chemical fertilizers and irrigation with organic fertilizers reduces the likelihood of being poor. Also, the adoption of improved seed combined with herbicide, improved seed with chemicals fertilizers and improved seed with organic fertilizers significantly reduce the probability of being poor. The combinations that enhance both food consumption and poverty status are irrigation and herbicide, irrigation and chemical fertilizers and improved seed and chemical fertilizers. Therefore, policy interventions should promote access to these technologies. Better targeting poor and vulnerable households must be the main channel to optimize the potential of agricultural technology intervention programs. While interesting results are found, this is limited as the time impact of agricultural technologies adoption on household food consumption and poverty status is not captured in this study. Further research may explore this link through a panel data model.

Disclosure statement

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

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