



Research article

Measuring the poverty reduction effects of adopting agricultural technologies in rural Ethiopia: findings from an endogenous switching regression approach

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ABSTRACT

The purpose of this study is to understand how the adoption of different agricultural technologies can reduce poverty in rural regions of Ethiopia. To attain this objective, this paper uses a comprehensive socio-economic survey of Ethiopia, which allows us to securitize the household level information. The paper uses a multinomial endogenous switching regression model to estimate the impact of alternative technologies adoption on poverty reduction on a sample of 2316 farm households, and a multinomial logit model to estimate the determinants of alternative agricultural technologies adoption. The results showed that the decision to adopt alternative agricultural technologies depends on several variables such as education, regional heterogeneity, remittance income, extension visit, credit access, off-farm activity, soil quality, farm size, tropical livestock unit, distance, plot's potential wetness, and ownership certification. The impact results of the study show that household consumption increases when households adopt alternative agricultural technologies, thereby reducing their poverty. Furthermore, adoption of a package of technologies can result in higher food and total consumption per adult than single technology adoption. The paper recommends strategies for further disseminating and scaling up these technologies to help reduce poverty in Ethiopia.

1. Introduction

Many experts now rightfully agree that goals related to sustainable development which includes SDG1 (regarding poverty), SDG2 (related to hunger), SDG3 (related to good health and wellbeing), SDG10 (inequality reduction), and SDG12 (regarding consumption and production) can be well addressed through the development of the agricultural sector. Different development organizations and governments consider agricultural technologies as a feasible way to improve the productivity of the farms and the agricultural sector. Currently, a wide range of agricultural technologies are being adopted around the world, but their adoption decisions are largely determined by the culture and local agricultural environment (Ruzzante et al., 2021). Specifically, when it comes to the developing countries of Africa, where agriculture provides the largest growth share, it is critical to look at the specific context of the country and determine that agricultural technologies are best suited to

address many of these sustainable development goals including SDG1 or no poverty. Given the African context, non-agricultural growth is not effective in decreasing poverty compared to agricultural growth, as the agricultural sector is more pro-poor than the non-agricultural sector (Diao et al., 2010). Hence, the agricultural sector is an important mechanism for reduction of poverty in African countries, and agricultural technologies can effectively address this issue.

In Ethiopia, agriculture is the dominant sector of the economy, providing livelihoods for the majority of the population (80%) and employing about 80% of the population. It also contributes significantly to the country's GDP (34.1 percent) as well as foreign income (79 percent), and the sector is the main basis of resources and capitals for investment in other sectors of the economy and markets (Diriba, 2020). But, the value addition of agriculture to GDP of the country is deteriorating through time (World Bank, 2020). This is mainly because the sector is constrained by farming which are small scale and rain fed,

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traditional farming systems and low adoption of modern technologies. Ethiopian rural farmers also have been facing the loss of soil fertility in their lands, and thus the agricultural sector is now challenged due to the low yields (Muluneh et al., 2022). Consequently, the country is still facing a huge food shortage, food insecurity, and a massive level of poverty (Kelemu, 2015). Many rural residents live under the national poverty threshold (33 percent), and another 14 percent of non-poor households are projected to fall into poverty (World Bank, 2015a). Hence, poverty reduction remains a major concern in Ethiopia, and improving agricultural productivity is one of the important basics of poverty reduction. For this reason, sustainable increases in agricultural productivity cannot be achieved without the adoption of agricultural technologies (Habtewold, 2021).

The adoption of alternative farming technologies shows a significant contribution in improving soil fertility, farmers' productivity, consumption, income, and overall farmers' welfare (De Janvry et al., 2017; Muluneh et al., 2022). As the green-revolution, lots of new or improved agricultural technologies have been introduced including improved techniques, high yield varieties, fertilizers, chemicals, machinery management, and many others, which all together increases farm productivity, income, consumption and improves household welfare in a consistent manner (Pingali, 2012; Ogundari and Bolarinwa, 2019). Owing to the critical role of agricultural technology in productivity, the Ethiopian government has given due consideration to the promotion and implementation of alternative new or improved agricultural technologies. Starting from the imperial government, the country has developed and executed various strategies to increase farm productivity by promoting agricultural technologies, for instance improved varieties, fertilizers, herbicides, pesticides, and value-added agricultural practices (Admassie and Ayele, 2010; Tefera et al., 2016). However, despite the efforts of the national government, the agricultural technology adoption rate remains lower and so far has not met the requirements (Alemu, 2020).

Past empirical studies have demonstrated that agricultural growth through improved and new agricultural technologies adoption is the most effective way to increase agricultural productivity, sustain food security and decrease poverty. The technology adoption in the sector of agriculture has greatly contributed to increased yields and improved household food security, thereby reducing household poverty (De Janvry et al., 2000, 2017; Kassie et al., 2018; Habtewold, 2021; Belay and Mengiste, 2021). Hence, various studies conducted around the world and in Ethiopia have suggested that agricultural technologies have the capability of reducing poverty in large scale. For example, the adoption of alternative farming technologies has been found to significantly increase yields, increase farm income, increase household consumption, improve nutrition, and generally improves household welfare (Sebsibie et al., 2015; Hagos, 2016; Tesfaye et al., 2016; Alwang et al., 2017; Belete and Melak, 2018; Akinrinola and Adeyemo, 2018; Adebayo et al., 2018; Ahmed and Anang., 2019; Verkaart et al., 2019; Natnael, 2019; Legesse et al., 2019; Tesfay, 2020; Biru et al., 2020; Teka and Lee, 2020; Abewa et al., 2020; Ayenew et al., 2020; Shita et al., 2020; Belay and Mengiste, 2021; Habtewold, 2021; Wordofa et al., 2021).

So, this study takes a novel attempt to see how the poverty reduction can be attained via technology adoption in the agricultural sector for Ethiopia. We undertake Ethiopia as a case study for several reasons. According to the report of the World Bank (2015b), while 30% of people in Ethiopia lived well below the poverty line in 2011, 30% population lived a day on less than 1.25 USD (PPP). However, the figure was 56% in 2000, making it one of the highest poverty rates globally. In a recent report, World Bank (2020) again demonstrated that the national poverty rate decreased to 24% in 2016. This poverty reduction has been possible due to significant growth driven by the country's agriculture sector for the past 16 years (World Bank, 2015b, 2020). From 2010-11 to 2014-2015, agriculture had the highest share of GDP among the three sectors such as agriculture, industry, and services. About 85% of employment is in the agricultural sector (Habtewold, 2021). But despite

this success rate in reducing poverty, it has also been reported that between 2012 and 2016, almost half of the rural Ethiopian population had to go through at least one spell of poverty. This suggests that consumption vulnerabilities and variability in rural areas still exist. These poor people have common characteristics in the sense that they are mostly the rural population that is also the households with a high level of dependency rates, and these households are headed by someone who has little education and older persons. But most importantly, they mainly work in the agricultural sector as well as casual labour to earn income and employment. Given the current contribution of agriculture to the Ethiopian economy and the high poverty rate that still exists in the rural region of the country, it is essential to note that agricultural growth will be critical for reducing poverty. Previous literature has well documented that this growth can come from agricultural technology, which will also ensure households' food security (Kassie et al., 2011; Habtewold, 2021).

In addition to the fact that we consider a distinct region for our study, there are several other ways in which this study adds to the empirical literature. First, although the literature on this topic is extensive, most studies examine the impact of single-farm technology, which is the unique contribution of this study. For example, Tesfaye et al. (2016) used improved wheat for Ethiopia, Alwang et al. (2017) used germplasm improvement research for two African countries, Belete and Melak (2018) used small scale irrigation technology for the Amhara region of Ethiopia, Ahmed and Anang (2019) used improved maize varieties for Ghana, Legesse et al. (2019) used better access to fertilizers for Ethiopia, Natnael (2019) used the Teff variety for Ethiopia, Tesfay (2020) used fertilizer for Ethiopia, Ayenew et al. (2020) used the wheat variety for Ethiopia, Shita et al. (2020) used chemical fertilizers and improved seeds for Ethiopia, Abewa et al. (2020) used the Teff variety for Ethiopia and Wordofa et al. (2021) used improved livestock and crop technologies for Ethiopia. However, farmers often tend to adopt single and combined alternative technologies at a time, and their choice to adopt these technologies is best considered through multivariate models (Biru et al., 2020). Hence, this paper evaluates the effect of adopting alternative technology packages (capture of organic fertilizer, inorganic fertilizer, and herbicides) on poverty in the study area. Given this, we wish to formulate the following research question:

RQ1: What determines the adoption of technology in agricultural sector decisions in Ethiopia's rural region?

Second, many previous studies studied the welfare effect of farm technology adoption using income as a proxy (e.g., Tesfaye et al., 2016; Adebayo et al., 2018; Ahmed and Anang, 2019; Natnael, 2019; Shita et al., 2020; Wordofa et al., 2021). However, previous literature suggests that household expenditure is a more consistent measure than household income (Rao, 2006). Hence, this paper uses consumption expenditure of the household as a proxy for poverty. Therefore, we wish to address the second and final hypothesis of this study:

RQ2: Does the adoption of agricultural technology matter for poverty reduction in rural Ethiopia?

Third, many prior studies have used Ordinary Least Squares (OLS), Tobit, and Matching models to estimate the effect of technology that are adopted in agriculture on the outcome variable (for example, Sebsibie et al., 2015; Hagos, 2016; Tesfaye et al., 2016; Alwang et al., 2017; Belete and Melak, 2018; Akinrinola and Adeyemo, 2018; Natnael, 2019; Abewa et al., 2020; Teka and Lee, 2020; Shita et al., 2020; Wordofa et al., 2021). But these approaches do not create enough counterfactuals and thus are not capable of providing adoption's actual impact. Also, here estimating the effect of technology adoption is difficult mostly due to selection bias owing to observables and unobservables factor (Belay and Mengiste, 2021). Hence, we implement a novel method to address these impact assessment pitfalls.

Fourth, this paper's findings can be the guidelines for countries experiencing poor agricultural productivity and wherein the poverty rates remain the highest. Fuglie et al. (2019) report that agricultural productivity is relatively stagnant in South Asia and Africa, where most of the poor live. Hence, there is an increasing need to improve their

livelihoods, especially those who live in rural areas. This issue can be achieved by investing heavily in new knowledge and technologies and ensuring they are properly adopted. About 80% people who are considered to be extremely poor live in rural region, where they depend primarily on agricultural activities. Therefore, if the governments of these countries want to achieve poverty reduction goals in these areas, the first priority should be to increase productivity through greater adoption of agricultural technologies. This issue mimics the situation in Ethiopia, where, as we have already mentioned, most of the poor live in rural areas where poverty is still rampant. So, by providing Ethiopia with a case study of how agricultural technologies can help improve household welfare, our results provide a powerful understanding of what is happening in other parts of the world, particularly South Asia and Africa. The results of this study can be used for future decision-making purposes for the poor countries of these regions and can greatly benefit scholars and professionals in these countries.

The continuing part of the study is arranged as follows: part two presents the method part, part three reports and discusses the study's results, and part four presents final concluding arguments.

2. Data description and research methodology

2.1. Data description

In this study, we apply a secondary dataset called Socioeconomic survey from Ethiopia or ESS which was collected in the years of 2015-16. The survey is representative of regional estimates for densely populated regions such as Oromia, Amhara, Tigray and SNNP (Southern Nation and Nationality people's). Consequently, this study considered all four representative regions. In addition, the data covers both rural and urban region; but, farmers in urban areas were excluded due to the non-practice of agricultural technology adoption. Therefore, we only take those households which are from rural Tigray, Amhara, Oromia, and SNNP. Hence, the survey included 220 rural enumeration areas from Tigray, Amhara, Oromia, and SNNP. Then, 12 households were selected from each enumeration areas, with no stratification for households engaged in cropping or livestock doings. However, during the data management process, 324 households were dropped because of missing information or absence/missing of farm households. To end, after adjustment and consideration for missing values, the total sample size of this paper is 2316 farm households for which full data are accessible.

The purpose of the current paper is carried out in two steps. Firstly, the role of different factors on the adoption behavior of different agricultural technology is analyzed. Secondly, using the MESR model, poverty-reducing impacts of alternative agricultural technology adoption are estimated. Table 1 provides the summary statistics of the explanatory variables used in this paper. Since our main objective is to estimate poverty-reducing impacts, this variable needs a special mention here. Household poverty is measured by two proxies in this study, one is household food consumption expenditure/adult/year and another one is total consumption expenditure/adult/year. Scholars have noted that a household's poverty status is measured consistently by its level of expenditure rather than its income since expenditure conveys information about how much it consumes, and the household also tends to misrepresent its income level (Rao, 2006). According to Rao (2006), the food expenditure method sets the poverty line by defining the food consumption outlay at which food energy intake is adequate to fulfill pre-determined minimum calorie requirements. However, this approach does not take into account the cost of non-food needs. Hence, this study considers both total consumption and food consumption approaches to assess the level of a household's poverty status.

One of the independent variables in this study is remittance income. In contrast to other forms of income, we focus on remittances for several reasons. In general, when remittances are sent, they directly go to the hands of the consumers and as a result, these remittances can reduce the

probability of a household falling into poverty. In Ethiopia, remittance contributes significantly to the national economy. However, due to a high level of informality (as much as 78%), inflows of remittances are not counted properly in this country. If these informal flows could be brought under formal channels, it will lead to a substantial decline in poverty than already estimated. Therefore, by measuring the effect of remittance on poverty, we provide a preliminary indication of that unobserved capability. Furthermore, according to the estimates from the World Bank, there are about 85 different countries where Ethiopians live so the country has a large diaspora abroad (Cooper and Esserm, 2018). Moreover, the remittances sent by the migrants account for one-quarter of the foreign exchange earnings of this economy. In the majority months of the year 2016, these remittances income even surpassed the export earnings of this country (Isaacs, 2017). We use the Foster Greer Thorbecke (FGT) poverty measure suggested by (Foster et al., 1984). This measure is usually written in Eq. (1) as:

$$P_{\alpha} = \frac{1}{N} \sum_{i=1}^q \left(\frac{z - y_i}{z} \right)^{\alpha} \quad (1)$$

In the formula, N represents total population per household no, z represents the threshold of poverty, y_i is the value of expenditure in consumption, and α is a parameter that is of aversion of poverty. Depending on the value of α , we can have severity index of poverty, depth of poverty as well as people who under or at the level of threshold.

2.2. Research methodology

2.2.1. Multinomial endogenous switching regression (MESR)

Measuring the impact of technology adoption decision on the outcome variables needs to control for issues such as that of heterogeneity which are not observed, bias in the selection as well as the problem of endogeneity. The MESR model addresses these impact assessment problems (Kassie et al., 2018). The model used here is adapted from (Kassie et al., 2015, 2018; Mohammed, 2014; Teklewold et al., 2017; Danso-Abbeam and Baiyegunhi, 2018; Biru et al., 2020). The adoption of alternative agricultural technologies and their implied effects on the outcome variable (e.g., productivity, food security and poverty) are modeled using the MESR model. Here, two sets of stages are considered. First, the multinomial logit model (MNL, here after) is used to investigate factors of alternative agricultural technologies adoption by rural farm households. Second, following to Dubin and McFadden (1984), the effect of adopting alternative agricultural technologies on the outcome variable is estimated using OLS, with the selectivity correction term as an additional regressor to account selection bias owing to time-varying unobserved heterogeneities. The inverse Mills' ratio is calculated from estimates of the MNL model and included in the outcome equations.

Table 2 presents the adoption of alternative technologies such as inorganic fertilizers, manures, herbicides, and their combinations, including an empty set for non-adoptions.

These 8 selection (adoption) equations were regressed by the MNL model. We suppose that at each time, a rational farmer adopts the technology that maximizes expected utility by comparing it with a package which is alternative called k. Having j (from 0 to 7) alternative choices, a farmer i decides to take on a technology if $U_{ij} > U_{ik}$ (Here, j is not equal to k).

U_{ij}^* is considered to be the utility which is expected and it is written in Eq. (2) below:

$$U_{ij}^* = Z_i \beta_j + \eta_{ij} \quad (2)$$

In the above equation, if it is the case that disturbance term has a distribution which is Gumbel and it is also identical, the equation for MNL written in Eq. (3) is:

Table 1. Definition, measurement of variables, and hypothesis of the study.

No	Variables ¹	Description	Value	Unit of measurement	Expected sign
Dependent variables:					
1	Adoption	At least a technology that is adopted by the household (Inorganic fertilizer, Manure, and Herbicide)	= 0 if no technology adopted, 1 inorganic fertilizer adopters, 2 manure adopters, 3 Herbicide adopters, 4 inorganic fertilizer & manure adopters, 5 inorganic fertilizer & herbicide adopters, 6 manure & herbicide adopters, 7 for those who adopt all the three technologies.		
2	Poverty	Poverty status of the household	= 1 if the household is poor and 0, for non-poor	Measured by household food and total consumption expenditure per adult equivalent in US dollar	
Independent variables					
1	Age	Head of the household age	Continuous	In years	+/-
2	Sex	Head of the household sex	Dummy	= 1 if Male, and 0 if Female	+/-
3	Family size	Size of families in the household	Continuous	In number	+/-
4	Education level	Education level of the household head	Continuous	Level of schooling years	+
5	Land size	Total Land size of the household	Continuous	In hectare	+
6	Distance to the market	Distance from home to the market	Continuous	In Kilometer	-
7	Distance to the zonal town	Distance from home to a zonal town	Continuous	In Kilometer	-
8	Distance to an all-weather road	Distance from home to the all-weather road	Continuous	In Kilometer	-
9	Livestock asset	Total livestock herd size	Continuous	In tropical livestock unit (TLU)	+
10	Credit access	Credit access to the household	Dummy	=1 if the household takes a loan; 0 if not	+
11	Extension contact	Extension services delivered by the agricultural offices	Dummy	=1 if the household gets extension contact during their practice; 0 if not	+
12	Advisory service	Getting Advice	Dummy	= 1 If the household gets advise; 0 if not	+
13	Remittance	Access to having remittance income	Continuous	=1 if the household receives, 0 if not	+/-
14	Off-farm Employment	Farmer's engagement with off-farm works	Dummy	=1 if the household participates; 0 if not	+/-
15	Plot distance	Distance from home to farm plots	Continuous	In kilometer	-
16	Plot PWI	Plot Potential wetness index used as a proxy for soil moisture	Continuous	Measured in Index	+
17	Soil quality	The plot Soil fertility quality	Categorical	= 1 if it is good, 2 is fair, and 3 if it is poor	+
18	Region	The four regions of Tigray, Amhara, Oromia & SNNP	Categorical	1 = if it is Tigray, 2 for Amhara, 3 for Oromia, and 4 for SNNP	+/-
19	Tenure security	Ownership of plots	Dummy	1= if households have their own plot; 0 if not	+

$$Prob(\eta_{ij} < 0 | Z_i) = \frac{\exp(Z_i \beta_j)}{\sum_{k=1}^J \exp(Z_i \beta_k)} \tag{3}$$

In the above equation, Z_i consists of all those variables that will help us determine what the factors responsible for adopting a particular technology are.

In the MESR model, the household food and total consumption (C) as a poverty proxy are regressed separately for non-adopters and adopters. Suppose C_j is an outcome variable and X_i is an explanatory variable for all the alternative packages. Here, C_j is observed when alternative j is adopted. There are 8 adoption packages; the reference group for this paper is non-adoption of any technologies ($F_0M_0H_0$), which is represented as $j = 0$. Whereas they are considered adopters if they adopt at

least one agricultural technology ($j = 1, 2, 3, \dots, 7$). The outcome equations for each regime j is then written in Eq. (4) as:

$$\begin{cases} \text{Regime 0 : } & C_{i0} = X_i \alpha_0 + \mu_{i0} \text{ if } j = 0 \\ \vdots & \vdots \\ \text{Regime } J : & C_{iJ} = X_i \alpha_J + \mu_{iJ} \text{ if } j = J, 1, 2, \dots, 7 \end{cases} \tag{4}$$

The linearity assumption of the Dubin and McFadden (1984) model can be specified as follows:

$$E(\eta_{ij} / \mu_{i0} \dots \mu_{ij}) = \sigma_j \sum_{k \neq j}^J \rho_j (\varepsilon_{ik} - E(\varepsilon_{ik})), \text{ where } \sum_{k \neq j}^J \rho_j = 0$$

According to (Di Falco et al., 2010), to get reliable estimates of MESR, if the residuals of η 's and μ 's are not independent and identically distributed, an estimation of OLS which is consistent, necessitates the addition of the selectivity correction terms (the mills ratio) of the alternative packages in Eq. (4). We can now say that correlation between error terms sum up to 0. Therefore, if this assumption is valid, we now specify

¹ They were selected based on (Admassie and Ayele, 2010; Sebsibie et al. 2015; Belay and Mengiste, 2021; Kassie et al., 2018; Tefera et al., 2016; Tesfay, 2020; Ayenew et al., 2020; Shita et al., 2020; Abewa et al., 2020; Wordofa et al., 2021).

Table 2. Alternative agricultural technology sets.

Choice	Adoption package	Inorganic Fertilizer (F)		Organic Manure (M)		Herbicide (H)		Frequency	Percentage
		F ₀	F ₁	M ₀	M ₁	H ₀	H ₁		
0	F ₀ M ₀ H ₀	✓		✓		✓		427	18.44
1	F ₁ M ₀ H ₀		✓	✓		✓		180	7.77
2	F ₀ M ₁ H ₀	✓			✓	✓		355	15.33
3	F ₀ M ₀ H ₁	✓		✓			✓	84	3.63
4	F ₁ M ₁ H ₀		✓		✓	✓		465	20.08
5	F ₁ M ₀ H ₁		✓	✓			✓	234	10.10
6	F ₀ M ₁ H ₁	✓			✓		✓	118	5.09
7	F ₁ M ₁ H ₁		✓		✓		✓	453	19.56
							Total	2316	100

Note: The adoption package is the combination of packages of different kinds, and adoption is determined by subscript 1 and 0 denotes that nothing is adopted. Household who have not adopted any technology is represented by Choice 0, those who adopt fertilizers that are inorganic are represented by 1, 2 for manure adopters, 3 for Herbicide adopters, 4 for inorganic fertilizer & manure adopters, 5 for inorganic fertilizer & herbicide adopters, 6 for manure & herbicide adopters, 7 is for those who adopt all the three technologies.

the consistent estimates of MESR can be specified and written in Eq. (5) as:

$$\begin{cases} \text{Regime 0 : } C_{i0} = X_i\alpha_0 + \theta_0\hat{\lambda}_{i0} + \xi_{i0} \text{ if } j = 0 \\ \vdots \\ \text{Regime J : } C_{iJ} = X_i\alpha_J + \theta_J\hat{\lambda}_{iJ} + \xi_{iJ} \text{ if } j = J, 1, 2, \dots, 7 \end{cases} \quad (5)$$

Where θ_j is the covariance between residuals of η_j 's and μ_j 's and λ_{ij} is the selectivity correction terms (mills ratio) from Eq. (3), specified in Eq. (6) and written as:

$$\hat{\lambda}_{ij} = \sum_{k \neq j} \rho_j \left(\frac{\hat{P}_{ik} \ln(\hat{P}_{ik})}{1 - \hat{P}_{ik}} + \ln(\hat{P}_{ij}) \right) \quad (6)$$

Here, correlation coefficient of our three disturbance term is ρ_j which has value of 0 as expected. P_{ij} is defined as the estimated probabilities in Eq. (3), or it is the likelihood that j option is taken by i household. There is a probability of facing heteroscedasticity problem in computing the mills ratio $\hat{\lambda}_{ij}$. Accordingly, the problem is solved by the use of bootstrapped standard errors.

We can now proceed towards the estimation of adoption of technology's treatment effect. Thus, from Eq. (5), counterfactual as well as actual values of expenditure in consumption can be written in Eqs. (7a, 7b, 7c, 7d) as:

1. Adopters with technology adoption (actual): -

$$E[C_{ij}|j=J] = X_{ij} \alpha_j + \theta_j \hat{\lambda}_{ij}, \quad j = 1, 2, \dots, 7 \quad (7a)$$

2. If the adopter decides not to adopt (counterfactual):

$$E[C_{i0}|j=J] = X_{ij} \alpha_0 + \theta_0 \hat{\lambda}_{ij}, \quad j = 1, 2, \dots, 7 \quad (7b)$$

3. Non-Adopters without technology adoption (actual):

$$E[C_{i0}|j=0] = X_{i0} \alpha_0 + \theta_0 \hat{\lambda}_{i0} \quad (7c)$$

4. If the non-adopter decides to adopt (counterfactual):

$$E[C_{ij}|j=0] = X_{i0} \alpha_j + \theta_j \hat{\lambda}_{i0} \quad (7d)$$

Now, we write the ATT or average treatment effect on treated is defined as the difference between Eqs. (7a) and (7b), and is given as:

$$ATT = E[E[C_{ij}|j=J] - E[C_{i0}|j=J]] = X_{ij}(\alpha_j - \alpha_0) + \hat{\lambda}_{ij}(\theta_j - \theta_0) \quad (8)$$

Average Treatment effect on Untreated (ATU) is defined as the difference between Eqs. (7d) and (7c) and can be written as:

$$ATU = E[E[C_{ij}|j=0] - E[C_{i0}|j=0]] = X_{i0}(\alpha_j - \alpha_0) + \hat{\lambda}_{i0}(\theta_j - \theta_0) \quad (9)$$

2.2.2. Exclusion restriction

Succeeding (Kraay, 2008; Di Falco et al., 2011; Verkaart et al., 2017), we have applied an exclusion restriction test to check whether the MESR model is adequately identified or not. The test works by excluding explanatory variables that are supposed to have a direct influence on the selection equation (the decision to choose the adopted strategy) while not on the outcome equations (consumption expenditures). This is because the mills ratio is a non-linear function of the exogenous variable in the selection equation and testing non-linearity is not simple. Therefore, to ensure the admissibility of the model, we have used distance from market, distance from zonal town, distance to all-weather road and plot distance, Plot PWI, extension visit, advisory service, off-farm participation, tenure security, soil quality, and the region as selection instruments. We have considered a falsification test to see and determine that these instruments are valid or not. As a result, the falsification test result of this study shows that the selected instruments are valid instruments.

2.3. Ethical considerations

Ethical approval for this study was obtained from the "Research ethics Approval committee of the Debre Berhan University, Ethiopia and authorized by the Department of Economics with Ref. No: CBE/01/01/778/2021. Informed consent was not sought for this study as the investigation was conducted through the use of secondary databases.

3. Results and discussion

3.1. Descriptive statistics

Table 3 reports the summaries of explanatory variables for the eight combined alternatives. The independent variables' average values of non-adopter households (F₀M₀H₀) are used as a reference group to compare with the average values of adopter households (F₁M₀H₀, F₀M₁H₀, F₀M₀H₁, F₁M₁H₀, F₁M₀H₁, F₀M₁H₁, and F₁M₁H₁ packages). The summary displays that the average values of different independent variables are significantly higher for adopters than the non-adopters. The average values of independent variables are also significantly different crosswise within adopters. The results indicated that all adopters had

Table 3. Summary of descriptive statistics.

Variables	$F_0M_0H_0$	$F_1M_0H_0$	$F_0M_1H_0$	$F_0M_0H_1$	$F_1M_1H_0$	$F_1M_0H_1$	$F_0M_1H_1$	$F_1M_1H_1$
	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
Food consumption	166.15	209.09	183.41	178.04	205.70	233.41	212.13	248.16
Total consumption	206.09	258.12	225.82	236.31	255.41	293.85	256.33	323.50
Sex	.639	.783***	.752***	.714	.80***	.794***	.771***	.834***
Age	49.18	49.13	50.49*	47.95	48.63	46.21***	48.07	48.69
Education	1.716	2.8***	1.912	1.964	2.49***	2.277***	2.161*	2.311***
Household size	4.302	4.916***	5.078***	4.440	5.447***	5.205***	5.144***	5.536***
Off-farm employment	.049	.083**	.076**	.071	.073**	.047	.084*	.052
TLU	2.230	4.018***	3.608***	4.064***	4.116***	5.403***	4.478***	5.630***
Remittance	.316	.238***	.301*	.178**	.258***	.239***	.245***	.218***
Distance to market	82.97	58.83***	82.12	80.60	66.29***	68.08***	76.22*	62.72***
Distance to Zonal town	202.17	176.06***	188.71***	232***	155.3***	175.1***	215.70	142.87***
Distance to all weather road	15.68	11.62***	20.24***	17.05	13.27***	13.27***	18.10*	12.22***
Extension visit	.028	.638***	.107***	.166***	.763***	.717***	.152***	.748***
Credit access	.063	.222***	.073	.154**	.232***	.294***	.144***	.346***
Advisory service	.391	.744***	.566***	.464*	.847***	.854***	.567***	.869***
Tenure security	.428	.594***	.594***	.488	.763***	.649***	.50*	.735***
Plot distance	1.111	.886*	.534***	.888*	2.279	.838***	.637***	.483***
Plot -PWI	12.39	12.60***	12.38	12.30	12.66***	12.72***	12.31	12.88***
Land size	.670	.982***	.769**	1.026***	.866***	1.427***	2.629	1.151***
Soil quality (good)	.442	.366**	.470	.404	.496**	.504**	.415	.507***
Soil quality (fair)	.475	.55**	.433*	.476	.443*	.444	.491	.423**
Soil quality (poor)	.081	.083	.095	.119	.060**	.051**	.093	.068

Note: Mean comparison test is used to compare the means of explanatory variables between non-adopters ($F_0M_0H_0$) and adopters of each packages of alternative technology, and the signs *, **, *** signifies significance level at 10%, 5%, and 1% respectively.

higher per adult-equivalent annual food and total consumption expenditures than non-adopters.

It is important to care, however, that these results do not justify the effect of technology adoption, as it may be due to other confounding factors. The same case can be argued for other variables as well. For example, a vector of household-related factors like the household head sex, the majority of adopter households are more male-headed households; for education, there is a significant difference with non-adopter, and the result shows that non-adopters have less schooling levels. In addition, the average size of the family for adopter household is larger than that of non-adopters. Furthermore, the mean household head age for adopting package ($F_1M_0H_1$) is lower than that of non-adopters.

The average farm size of adopter household is significantly higher than that of non-adopter households. For adopters, the average livestock size of the household and the percentage of farm households participated in off-farm works are much higher. On average, the share of remittance receiver farm households is significantly larger for non-adopters. Furthermore, access to infrastructure like roads and distance to market is deemed important in determining farmers' likelihood of technology adoption. In this regard, the average distance from markets, all-weather roads, and the zonal town are significantly larger for non-adopters. Finally, explanatory variables for instance extension and advisory

services, advisory access to credit, and land ownership right are significantly linked with the adoption of alternative agricultural technology packages. In addition, adopters ensured that the mean value of the potential wetness index of the plot was significantly higher, and the mean distance from the plot to the farmhouse was lower than their counterfactuals. The proportion of adopters' good soil quality was found to be statistically higher for adopters.

Average comparisons show some heterogeneity between alternative technology adopters and non-adopters, so providing non-adopters with the same incentives as adopters would enable them to adopt agricultural technologies and improve their welfare. Specifically, helping the non-adopters through creating awareness and providing extension services about the applicability and benefit of alternative agricultural technologies; expanding the access to infrastructure, market, and service centers; providing access to credit, and channeling remittance income to invest in agriculture is needed.

Finally, regional location is also considered as a factor affecting the probability of agricultural technology adoption by farmers, as shown in Figure 1. The summary shows that, inorganic fertilizer adoption ($F_1M_0H_0$) is higher in Oromia (32.2%) followed by Amhara (28.3%), Tigray (23.3%), and SNNP (16.1%); organic fertilizer ($F_0M_1H_0$) adoption is higher in SNNP (36%) followed by Amhara (32.9%), Oromia (18%)

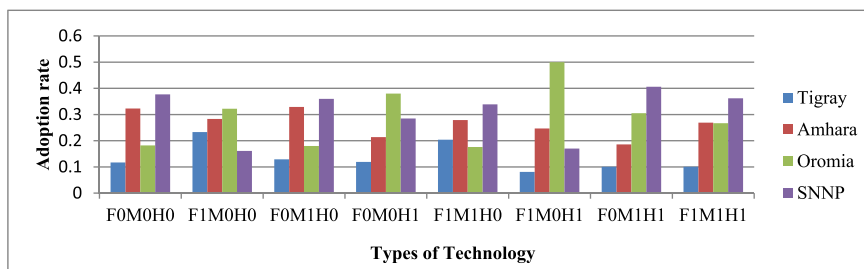


Figure 1. Agricultural technology adoption by region.

Table 4. Determinants of Agricultural technology adoption.

Variables	Alternative technology Adoption Packages						
	$F_1M_0H_0$	$F_0M_1H_0$	$F_0M_0H_1$	$F_1M_1H_0$	$F_1M_0H_1$	$F_0M_1H_1$	$F_1M_1H_1$
	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)
Sex	-0.023 (0.260)	0.164 (0.191)	0.043 (0.300)	-0.234 (0.217)	-0.238 (0.257)	0.171 (0.270)	0.011 (0.227)
Age	0.006 (0.008)	0.009 (0.005)	-0.008 (0.009)	-0.003 (0.006)	-0.021*** (0.007)	0.001 (0.008)	-0.006 (0.007)
Education	0.116*** (0.032)	0.034 (0.027)	0.004 (0.040)	0.098*** (0.029)	0.032 (0.032)	0.017 (0.037)	0.058* (0.030)
Household size	-0.013 (0.055)	0.106*** (0.040)	-0.112 (0.067)	0.077* (0.045)	-0.049 (0.051)	0.027 (0.055)	0.026 (0.046)
Off-farm employment	0.410 (0.391)	0.537* (0.322)	0.418 (0.494)	0.368 (0.355)	-0.137 (0.463)	0.574 (0.418)	0.130 (0.374)
TLU	0.091* (0.050)	0.094*** (0.034)	0.105*** (0.037)	0.080** (0.036)	0.126*** (0.036)	0.113*** (0.037)	0.175*** (0.036)
Remittance	-0.047* (0.028)	-0.040** (0.020)	-0.024 (0.031)	-0.036*** (0.011)	-0.028* (0.017)	-0.048 (0.034)	-0.038** (0.017)
Distance to market	-0.005** (0.003)	0.001 (0.002)	-0.000 (0.003)	-0.005** (0.002)	-0.001 (0.003)	-0.006** (0.003)	-0.006*** (0.002)
Distance to zonal town	-0.005*** (0.001)	-0.003*** (0.001)	-0.000 (0.001)	-0.007*** (0.001)	-0.008*** (0.001)	-0.001 (0.001)	-0.010*** (0.001)
Distance to road	-0.020** (0.009)	0.017*** (0.005)	0.005 (0.008)	-0.007 (0.006)	-0.005 (0.008)	0.015** (0.007)	-0.004 (0.007)
Extension visit	4.051*** (0.376)	1.128*** (0.370)	1.814*** (0.437)	4.612*** (0.357)	4.324*** (0.385)	1.579*** (0.408)	4.520*** (0.363)
Credit access	0.841*** (0.311)	-0.290 (0.290)	0.760** (0.374)	0.669** (0.280)	1.150*** (0.298)	0.561 (0.354)	1.241*** (0.278)
Advisory service	0.394* (0.239)	0.492*** (0.162)	-0.019 (0.270)	0.683*** (0.199)	0.876*** (0.257)	0.321 (0.226)	0.759*** (0.214)
Tenure security	0.507** (0.227)	0.553*** (0.167)	0.413 (0.267)	1.340*** (0.198)	0.994*** (0.221)	0.311 (0.243)	1.085*** (0.203)
Plot distance	-0.004 (0.004)	-0.323*** (0.083)	-0.004 (0.012)	-0.002 (0.002)	-0.006* (0.003)	-0.125 (0.085)	-0.382*** (0.124)
Plot PWI	0.053 (0.081)	0.029 (0.065)	-0.093 (0.089)	0.072 (0.071)	0.091 (0.091)	-0.050 (0.106)	0.181** (0.076)
soil quality (fair)	0.590*** (0.218)	-0.032 (0.162)	0.114 (0.267)	0.215 (0.181)	0.107 (0.211)	0.237 (0.236)	0.313* (0.189)
soil quality (poor)	0.532 (0.384)	0.275 (0.279)	0.294 (0.435)	0.090 (0.336)	-0.294 (0.439)	0.250 (0.408)	0.491 (0.349)
Land size	0.025 (0.096)	-0.105 (0.109)	0.104 (0.080)	-0.073 (0.102)	0.120 (0.077)	0.128* (0.076)	0.012 (0.089)
Region Amhara	-0.520 (0.322)	-0.096 (0.263)	-0.489 (0.422)	-0.354 (0.293)	0.422 (0.390)	-0.457 (0.421)	0.357 (0.316)
Region Oromia	0.734* (0.376)	0.016 (0.332)	0.809* (0.480)	0.692* (0.360)	2.740*** (0.434)	0.680 (0.452)	2.018*** (0.376)
Region SNNP	-0.608* (0.348)	-0.188 (0.280)	-0.004 (0.455)	0.440 (0.302)	0.505 (0.421)	0.564 (0.422)	1.267*** (0.325)
Constant	-2.401* (1.252)	-1.999** (0.983)	-0.607 (1.343)	-2.586** (1.094)	-2.901** (1.356)	-1.821 (1.595)	-4.276*** (1.155)

Model VCE = Robust; Pseudo R² = 0.2222; Number of observation = 2316; SE is standard error in parenthesis; the signs (*, **, ***) represents significant levels at 10%, 5%, and 1% respectively.

and Tigray (12.9%); herbicide ($F_0M_0H_1$) adoption is higher for Oromia (38%) followed by SNNP (28.5%), Amhara (21.4%) and Tigray (11.9%); $F_1M_1H_0$ is higher in SNNP followed by Amhara, Tigray, and Oromia; $F_1M_0H_1$ is higher in Amhara followed by SNNP, Oromia and Tigray; $F_0M_1H_1$ is higher in Amhara and Tigray followed by SNNP and Oromia; and full package adopters are higher in the region of SNNP (36.2%) followed by Amhara (26.9%), Oromia (26.7%) and Tigray (10.1%).

3.2. Determining factors of adopting agricultural technology

Before estimating the MNL, we applied specification and validity tests of the model. First, the results of the Wald's test accepts the alternative hypothesis that all regression coefficients are together different from zero with $[\chi^2(154)=(1069.657); P > 0.000]$. Second, the Hausman IIA test of the dependent category checks that all the different technology packages are distinguishable with respect to the variables in the model.

Table 4 provides the MNL estimation result. The base category of the model is non-adoption ($F_0M_0H_0$), in which the adoptions of alternative technologies are compared. The result shows that the age household head is negatively influencing the likelihood of adopting $F_1M_0H_1$ package, showing that young households are more expected to adopt $F_1M_0H_1$ package than old farm households because young households can have better educational level and are less risk-averse than the old farm households. The result is similar to [Habtewold \(2021\)](#) and [Ayenew et al. \(2020\)](#). Household head's education positively affects the adoption of package $F_1M_0H_0$, $F_1M_1H_0$, and $F_1M_1H_1$, implying that educated households are expected to adopt $F_1M_0H_0$, $F_1M_1H_0$, and $F_1M_1H_1$ than the non-adopters. Because educated farmers can access, scrutinize and assess information about different agricultural technologies, market opportunities, and benefits of the technologies. This result falls in a similar line to that of [Adebayo et al. \(2018\)](#) and [Feyisa \(2020\)](#).

On the other hand, household family size has a significant positive influence on the likelihood of adopting $F_0M_1H_0$ and $F_1M_1H_0$ packages, implying that farm households with larger family sizes are more expected to adopting $F_0M_1H_0$ and $F_1M_1H_0$ packages than their counterfactuals. This is for the reason that adopting technologies like $F_0M_1H_0$ and $F_1M_1H_0$ packages needs and invites more labour force for farming activities. The result is parallel with the works of [Tefera et al. \(2020\)](#) and [Shita et al. \(2020\)](#). Livestock wealth, as measured by TLU, has a significant positive effect on the adoption of all technology packages considered in this paper, meaning that farmers with large livestock assets were expected to adopt more than farmers with fewer livestock assets. This is because livestock farming is a means of improving technology through sources of income and agricultural inputs such as manure fertilizer. The result is in line with the findings of [Admassie and Ayele \(2010\)](#) and [Biru et al. \(2020\)](#).

Households' off-farm work participation has a significant positive effect on the adoption of $F_0M_1H_0$ package, indicating that farmers who join in off-farming works are more expected to adopt $F_0M_1H_0$ than their counterparts. The result is parallel with the findings of [Alwang et al. \(2019\)](#) and [Ayenew et al. \(2020\)](#). The variable remittance has a significant negative effect on the adoption of $F_1M_0H_0$, $F_0M_1H_0$, $F_1M_1H_0$, $F_1M_1H_1$ technology packages. It is for the reason that those farm households receiving remittances are less probable to adopt agricultural technologies than their counterfactuals. One plausible reason for the negative effect of remittances on technology adoption might be the household's way of using the income from the remittances. In many cases, remittance incomes will be allocated for consumption rather than investment in agricultural growth. The result is consistent with the findings of [Tuladhar et al. \(2014\)](#) and [Zegeye \(2021\)](#).

Distance to the market has a significant negative influence on adopting $F_1M_0H_0$, $F_1M_1H_0$, $F_0M_1H_1$, and $F_1M_1H_1$ technology packages. Again, distance to all roads has a significant negative influence on the probability of adopting $F_1M_0H_0$, and a significant positive effect on the likelihood of adoption of $F_0M_1H_0$ and $F_0M_1H_1$ packages. In addition, distance to the zonal town has a significant negative influence on the

probability of adopting $F_1M_0H_0$, $F_0M_1H_0$, $F_1M_1H_0$, $F_1M_0H_1$, and $F_1M_1H_1$ packages. This concludes that farm households who live far from service centers (e.g. towns, agricultural development agencies, and markets) have lower probability of adopting agricultural technology than those who live near these centers. This is because farmers who live far from these centers could have less information access about the availability and adoption of agricultural technology and higher production costs. And, due to longer road distances, farmers use technologies that are available nearby, such as organic fertilizers, and easily portable technologies, such as herbicides, to minimize production costs. This result is consistent with the findings of ([Admassie and Ayele, 2010](#); [Belay and Mengiste, 2021](#); [Tefera et al., 2020](#); [Shita et al., 2020](#); [Wordofa et al., 2021](#)).

Gaining extension access had a significant positive influence on the probability of adopting all technology packages, suggesting that those farm households with extension visits were more expected to adopt the technology than those without. This is because extension contacts benefit households in increasing their knowledge of the description and characterization of farm technologies, adoption, and impact of the technologies. It also provides pleasing information, agricultural training, and farming advice services on the sources of agricultural technology and the importance of technology to households, and on the distribution of inputs. Advisory service has a significant positive effect on the adoption of $F_1M_0H_0$, $F_0M_1H_0$, $F_1M_1H_0$, $F_1M_1H_1$, and $F_1M_1H_1$ packages, implying that those farmers who received consulting services were more likely to adopt than those who did not. This is because the regular advisory services of agricultural development agencies, farm associations and conferences play a vital role in the diffusion and adoption of agricultural technologies. The result is parallel with the works of [Feyisa \(2020\)](#), [Habtewold \(2021\)](#), [Tefera et al. \(2020\)](#), and [Belay and Mengiste \(2021\)](#). The variable credit access has a significant positive effect on the probability of adopting $F_1M_0H_0$, $F_0M_0H_1$, $F_1M_1H_0$, $F_1M_1H_0$, and $F_1M_1H_1$ technology packages, showing that those farm households who have taken loans are more expected to adopt than their counterparts. This is for the reason that getting credit access can address income limitations that farm households may face when purchasing alternative agricultural technologies, thereby opening the way for timely adoption. The result is similar to the works of [Belete and Melak \(2018\)](#), [Ayenew et al. \(2020\)](#), and [Belay and Mengiste \(2021\)](#).

Tenure security has a significant positive effect on the likelihood of adoption of $F_1M_0H_0$, $F_0M_1H_0$, $F_1M_1H_0$, $F_1M_1H_0$, and $F_1M_1H_1$ packages, implying that farm households with land certificates are more expected to adopt than those without. This is because having an ownership right for their land helps the farm households create a long-term investment and could have no additional costs (because when farmers are landless, they may have an additional rental cost; in such cases, they will not be interested in adopting). This result is similar with the findings of [Mohammed \(2014\)](#). As compared to the good soil quality (which is used as a reference), fair soil quality has a significant positive influence on the probability of adopting $F_1M_0H_0$ and $F_1M_1H_1$ packages, signifying that farmers who have plots with fair soil quality are more likely to adopt than those who have plots with good soil quality. This may be because farmers bear the cost of adopting agricultural technologies only if they expected to improve the soil quality and gain greater returns from the adoption of alternative agricultural technologies. The result is parallel to the findings of [Sebsibie et al. \(2015\)](#) and [Ayenew et al. \(2020\)](#).

Distance from plot to farmhouse has a significant negative influence on the probability of adopting $F_0M_1H_0$, $F_1M_0H_1$, and $F_1M_1H_1$ packages, suggesting that farmers farther away from plots or fields were less likely to adopt than their peers. This is because the farther the household's plot is from the farmhouse, the less likely it is to make a prompt decision about plot preparation, weeding, harvesting, and input use. The result is consistent with the findings of [Sebsibie et al. \(2015\)](#) and [Tefera et al. \(2020\)](#). In addition, the potential wetness index of the plot has a significant positive effect on the likelihood of adopting full technology package ($F_1M_1H_1$). This is for the reason that as the soil moisture, soil PH value,

Table 5. Average treatment effects of adoption on consumption expenditure (US\$²).

	Technology set	Annual Adult equivalent food consumption expenditure			Annual adult equivalent Total consumption expenditure		
		Decision stage		Treatment Effect	Decision stage		Treatment effect
		To Adopt	Not to adopt		To Adopt	Not to Adopt	
				ATT			ATT
Farm Households that Adopted	F ₁ M ₀ H ₀	209.09 (.104)	172.59 ¹ (.108)	36.81***	258.12 (.132)	211.60 ¹ (.158)	46.52***
	F ₀ M ₁ H ₀	183.41 (.063)	149.29 ² (.064)	34.12***	225.82 (.076)	181 ² (.090)	44.82 ***
	F ₀ M ₀ H ₁	178.04 (.102)	180.11 ³ (.132)	-2.07	236.31 (.144)	220.96 ³ (.185)	15.35*
	F ₁ M ₁ H ₀	205.70 (.066)	152.34 ⁴ (.059)	53.36***	255.41 (.085)	178.75 ⁴ (.086)	76.66***
	F ₁ M ₀ H ₁	233.41 (.085)	180.19 ⁵ (.103)	53.22***	293.85 (.115)	212.12 ⁵ (.141)	81.73***
	F ₀ M ₁ H ₁	212.13 (.136)	178.04 ⁶ (.333)	34.09**	256.33 (.166)	224.60 ⁶ (.556)	31.73
	F ₁ M ₁ H ₁	248.16 (.083)	155.28 ⁷ (.065)	92.88***	323.50 (.105)	177.33 ⁷ (.088)	146.17***
				ATU			ATU
Farm Households that didn't Adopt	F ₀ M ₀ H ₀	205.98 ¹ (.087)	166.15 (.056)	39.83***	258.99 ¹ (.116)	206.09 (.078)	52.90***
	F ₀ M ₀ H ₀	193.01 ² (.092)		26.86***	242.75 ² (.119)		36.66***
	F ₀ M ₀ H ₀	177.60 ³ (.046)		11.45***	252.82 ³ (.085)		46.73***
	F ₀ M ₀ H ₀	317.56 ⁴ (.097)		151.41***	393.53 ⁴ (.116)		187.44***
	F ₀ M ₀ H ₀	235.21 ⁵ (.086)		69.06***	341.98 ⁵ (.152)		135.89***
	F ₀ M ₀ H ₀	209.17 ⁶ (.085)		43.02***	254.98 ⁶ (.086)		48.89***
	F ₀ M ₀ H ₀	350.83 ⁷ (.132)		184.68 ***	456.86 ⁷ (.155)		250.77***

Note: Standard errors in parenthesis; and *, ***, represents significance level at 10% and 1% respectively.

Table 6. FGT - poverty measures by technology adoption.

Packages	Using Food Consumption Expenditure/adult/annum			Using Total Consumption Expenditure/adult/annum		
	Headcount	Depth	Severity	Head count	Depth	Severity
F ₀ M ₀ H ₀	0.73536	0.33369	0.19286	0.89696	0.44999	0.27217
F ₁ M ₀ H ₀	0.62222	0.25049	0.12789	0.78333	0.34688	0.19179
F ₀ M ₁ H ₀	0.72113	0.32598	0.18985	0.84225	0.42477	0.25778
F ₀ M ₀ H ₁	0.64286	0.30116	0.19521	0.76190	0.36621	0.23688
F ₁ M ₁ H ₀	0.66667	0.27999	0.14822	0.81075	0.38077	0.21611
F ₁ M ₀ H ₁	0.50855	0.18685	0.09510	0.73504	0.27246	0.13656
F ₀ M ₁ H ₁	0.66949	0.28220	0.15293	0.77966	0.38172	0.22560
F ₁ M ₁ H ₁	0.57395	0.19799	0.08979	0.71523	0.26986	0.12911

ground water level and humidity of the plot raises the more expected to adopt F₁M₁H₁ technology package. The result is parallel with [Tefera et al. \(2020\)](#). Household farm size has a significant positive influence on the probability of adoption of package F₀M₁H₁, meaning that households with large farm sizes are more likely to adopt F₀M₁H₁ package than those with smaller farm sizes. Because as the size of operating farms increases, farmers are more likely to see farming activities as permanent or a means of life: thus more expected to adopt alternative technology packages. This means that larger farmland size can act as insurance counter to the risk of crop failures. This finding is consistent with [Alwang et al. \(2019\)](#) and [Feyisa \(2020\)](#).

Lastly, the regional location variable is considered as a factor that determines the household's technology adoption, and this helps to see whether regional heterogeneity matters in the adoption decision or not. As compared with Tigray region (which is used as a reference), households in the Oromia region are more likely to adopt F₁M₀H₀, F₀M₀H₁, F₁M₁H₀, F₁M₀H₁ and F₁M₁H₁ packages. In contrast, farm households in the SNNP region are less probable to adopt F₁M₀H₀ and more likely to adopt F₁M₁H₁. This validates the hypothesis that agricultural technology adoption is affected by location (regional differences). The positive impact shows that these regions have favorable agricultural policies that support farmers in adopting these agricultural technologies to increase

agricultural production and productivity. These supports may consist of provision of infrastructure (i.e. road access), advisory services, access to information, access to credit, timely supply of inputs at a fair cost, technical support and other incentives. The result is parallel with the findings of [Tefera et al. \(2016, 2020\)](#) and [Habtewold \(2021\)](#); regional dummy variables are associated with the likelihood of the agricultural technology adoption decisions, possibly reflecting unobservable spatial differences.

3.3. Poverty reducing impacts of technology adoption

Here, the study estimates the poverty reducing impacts of alternative agricultural technology adoption using the MESR model. Using this model, the study estimated annual food and total consumption expenditure/adult equivalent. The paper then plugs the coefficients of the annual food and total consumption/adult equivalent functions in equations (m₀-m₇) in the outcome equations to produce selectivity-correction predictions obtained from the MNL model. In the estimation results of the MESR model, an additional regressor, the mill ratio, is significant, indicating a self-selection bias in technology choices. This means that adopting different alternative technologies won't have the same impact on non-adopters, whether they choose to adopt, as it does on alternative technology adopters. This proves that using an ESR model is appropriate. The falsification test result checks that the selected instruments are valid and confirms that the MESR model has been effectively identified.

² 1US\$ =20.68 Ethiopian local currency (ETB) on average during the survey periods.

Table 5 shows the expected value of annual food and total consumption expenditure per adult equivalent, along with the average treatment effect, under actual and counterfactual scenarios. The results indicate that there are significant differences in consumption between the adopter and non-adopter farm households. This means that adopters have higher per adult annual food and total consumption expenditures compared to non-adopters. The highest impact is observed when adopters combined these technologies. Specifically, the highest food and total consumption expenditures are obtained when farmers adopted full packages (\$248.16 and \$323.50), followed by when farmers adopted a combination of inorganic fertilizer and herbicide (\$233.41 and \$293.85), respectively. The second-largest food and total consumption expenditure (\$212.12 and \$ 256.33) is gained when farm households adopted a mix of organic fertilizer and herbicide packages, followed by when farmers adopted inorganic fertilizer (\$209.09 and \$258.12) and a mix of organic and inorganic fertilizers (\$205.7 and \$255.41) respectively. Here, it's important to stress that agricultural technologies only increases consumption expenditure if it's accompanied by other technologies. The lowest food and total consumption expenditure are gained when farm households adopted a single technology of organic fertilizer and herbicides respectively. However, it is still larger than the non-adopters' food and total consumption expenditure (\$166.15 and \$206.09), respectively. Overall, the results confirm that adopter farm households of any combination of different technology packages have larger food and total consumption expenditure/adult/year than non-adopters households.

The adoption effect on adopters shows that farm households who adopted would have significantly less annual food and total consumption expenditure/adult/year if adopters were non-adopters. Conversely, the adoption effect on non-adopters shows that households who had not adopted ($F_0M_0H_0$) would have a larger amount of food and total consumptions/adult/year if they were to adopt it, compared to the actual adopters.

3.4. Poverty measures by technology adoption

Here, we want to show the link between agricultural technology adoption and rural poverty and answer the question, "overall, has technology adoption reduced the poverty of farm households?" By using cross-sectional data and multinomial endogenous switching regression model, we have estimated the poverty-reducing impacts of adoption of alternative agricultural technologies in the study area. To compare the poverty difference between agricultural technology adopter and non-adopters, the study used national food and total poverty thresholds of \$211.79 and \$347.38 per adult per annum (Natnael, 2019). Table 6, presents the FGT poverty measure result and it shows that adoption has a significant effect on raising farm households' food and total consumption expenditure/adult/annum, resulting in reduced household poverty headcount, gap, and severity of poverty relative to non-adopting households. Any of the adopters have lower values in terms of poverty headcount (the proportion of poor is lower in adopters), poverty gap (the mean distance from the poverty line is lower for adopters), and squared poverty gap (the lower inequality among the poor for adopters) as compared to the non-adopters. Thus, adoption significantly reduces the total consumption gap for the poor by increasing their food and total consumption. It can be expected that their consumption will gradually increase to the level needed to escape poverty. Within adopters, adopters of $F_1M_1H_1$, $F_1M_0H_1$, and $F_1M_0H_1$ are less severely poor than others, respectively. This proves that combined technology adopters have less poverty severity, and that adoption is more effective in reducing poverty than single technologies. This is in line with Hörner and Wollni (2020), who found that the use of combined farming technologies pays off better than single technologies because of their synergistic effects. The application of combined technologies can significantly increase land productivity and, in turn, increase household crop yields. In another study, Hörner and Wollni (2021) found that household income as well as food security increased with the adoption of integrated technology in

Ethiopian highlands. Using multinomial ESR approach, Levy and Ngeno (2021) also observed that combining multiple agricultural technologies can improve nutritional outcomes in wasting, underweight and stunting. These nutritional outcomes are related to a person's intake of food energy and nutrients. Our study's findings is also consistent with De Janvry and Sadoulet (2002) who have demonstrated that there are two ways agricultural technologies can affect household poverty. First, it can increase the food that households consume as well as the marketable surplus, which in turn affects vulnerability to poverty and poverty. This is a direct impact. Another effect is indirect, which is gained from an increase in output produced, which leads to lower food prices in the food market and affecting poverty.

4. Conclusions and discussion

The core objective of this study is to estimate the poverty-reducing impact of the adoption of alternative agricultural technologies, especially the adoption of inorganic fertilizers, organic manures, herbicides, and their combinations, on household food and total consumption expenditures in Ethiopia. The paper uses data from the 2015/16 Ethiopian Socio-Economic Survey on 2,316 farming households. We estimated multinomial logit model to examine factors that affect households' decision-making on the adoption of alternative agricultural technologies, and Multinomial Endogenous Switching Regression model to measure the impact of adoption on poverty, measured through food and total consumption expenditure per adult equivalent per annum.

The results of this paper lead to the following key conclusions. First, a household's adoption decision of agricultural technology is mainly affected by household socioeconomic characteristics, availability of information access, institutional characteristics, plot characteristics, distance and geographic locations. Specifically, adoption decision is positively affected by education of the head, off-farm work activity, tropical livestock unit, extension visit, credit access, advisory service, tenure security, land size, fair soil quality, and plot potential wetness; and negatively affected by distance from market, from zonal town, from all-weather roads and plot distance, and remittance. Second, the multinomial switching regression model shows that, on average, adopters of any combination of agricultural technologies have larger annual food and total consumption expenditure per adult than the non-adopters and in addition they have lower poverty headcount, depth, and severity. Moreover, the highest annual food and total consumption expenditure are obtained when farmers adopt by combined technologies like; inorganic fertilizer, organic manure, and herbicide; inorganic fertilizer and herbicide; manure and herbicide, and manure and inorganic fertilizer than adopting a single agricultural technology. In conclusion, the study results reveal that adoption of agricultural technologies have positive and significant effect on increasing household food and total consumption expenditure/adult/year, thereby reducing poverty.

4.1. Contribution of the study

This study adds to the existing literature in a number of ways. Firstly, we focus on rural Ethiopia, where poverty reduction efforts are still rampant despite a significant decrease in urban areas. Ethiopia's strong and rapid economic growth was well pronounced in urban areas through the increase in consumption growth but not so much in rural areas. While the urban poverty rate fell from 26 percent in 2011 to 15 percent in 2016 (a decrease of 11 percent), the poverty rate in rural areas fell by only 4 percentage points (World Bank, 2020). Therefore, in this study we focus on rural areas in Ethiopia to understand how improving agricultural productivity through the adoption of technology can eliminate poverty in rural areas.

In addition, poverty reduction has been at the top of many development agendas around the world, including SDGs adopted in 2015, which lists no poverty as the first SDG goal to be achieved within 2030. It is documented that many of the world's poor farmers are smallholders, and

the agriculture sector provides them with food, employment, and income. Therefore, the development of the agricultural sector is very important and a must to reducing poverty in these poor countries. Studies show that agricultural technology can pave the way for improving household welfare, especially for smallholder farmers (Habtewold, 2021). Thus, although our paper focuses on the rural region of Ethiopia, the study's policy implications can be generalized for achieving SDG1 in other countries as well.

Secondly, previous literature has primarily exploited the effects of single-farm technology adoption in research. But farmers are likely to adopt different combinations of technologies at the same time, especially in rural areas. Therefore, we focus on single and multiple agricultural technologies and their impact on poverty. Thirdly, in contrast to previous studies, we use two proxies of poverty in this study: household food consumption expenditure and total consumption expenditure. We do not focus on income for measuring poverty, which has been proven to be misrepresentative of a household's status in many survey studies. Fourthly, again, many studies have studied the impact of adoption of different agricultural technologies on household welfare; they have used the PSM approach. However, here we use the multinomial ESR method. The choice of ESR over PSM is because the PSM controls for selection bias caused by observables only and does not account for unobservable. In this regard, the ESR model controls for selection bias caused by both observable and unobservables (Tiruneh and Wassie, 2020). Other than that, ESR is best at building good counterfactuals on PSM. This implies that the ESR model is better to compare the expected consumption expenditure of adopters relative to non-adopters and to investigate the expected consumption expenditure in the actual and counterfactual scenarios (Asfaw and Shiferaw, 2010).

4.2. Policy implications

Based on the above discussion, several policy recommendations can be made. Policies aimed at encouraging and expanding the adoption of new or improved agricultural technologies and agricultural technology mixes will have a significant impact on improving household consumption expenditures, thereby reducing poverty in Ethiopia. Therefore, governments at both central and local levels should strengthen interventions at the local policy level to expand credit access and agricultural extension services. Smooth access to agricultural credit from the public and private financial institution will enable farmers with the opportunity to adopt these technologies. In addition, the extension visits and advisory services should be significantly expanded. In this regard, the development of Information and communication technology (ICT) is essential, which will not only provide information about the improved agricultural technologies but will also allow farmers to seek and get advice easily and with smaller costs. With regard to remittances, we have found a negative effect on the adoption of technology, primarily because the remittances are mainly utilized for consumption purposes. Hence, the government should encourage farmers to use remittances to invest in different farming technologies, which will increase household welfare in the long term. Educating farmers in this regard is essential, as they may not understand the indirect impact of remittances on their welfare. Education will help farmers understand the potential pros and cons of adopting improved and new farming techniques without any intermediaries. Hence, the government should invest more and updating the system through time to improve the literacy rate of rural farmers.

We also found that household size positively affects the probability of adopting $F_0M_1H_0$ and $F_1M_1H_0$ packages, both of which are labor-intensive technologies. This supports the claim of Grabowski et al. (2016) that family or household size is a constraint on the adoption of labor-intensive technologies. Hence, shifting from any other technology to these technologies will require significant labor investment, and governments, private organizations, cooperatives, and other

stakeholders should keep this in mind when encouraging these technologies. Rather than focusing on extensive farming, it is suggested that more emphasis should be placed on increasing climate-smart farming technologies and different agroforestry practices. In terms of plot distance, it was found that the greater the distance between the plot and the farmers, the lower the adoption of technology between them. Therefore, the government should seek different alternatives through which complementary inputs can be accessed. For example, infrastructure access should be developed.

With regard to farm size, it influences the adoption of technology positively. In our study, we did not consider the impact of farm size on environmental or soil quality, as we were only concerned with how technology affects welfare. But previous research has shown that smallholder farming systems are more likely to be beneficial for the environment. Therefore, our results should be treated with caution. The government should strike a balance between encouraging smallholder farmers and those with larger farms. On the one hand, it should encourage large-farm-scale farmers to adopt environmentally-friendly farming technologies, and on the other hand, there is clearly a growing need to develop farming technologies that smallholder farmers can adopt. Therefore, governments should focus on reducing the fixed adoption costs for smallholders so that they can adopt these technologies. This balance is thought to ensure sustainable production, which is beneficial for the environment and farmers.

4.3. Limitations of the study

Data limitations have hindered the study not to consider agricultural technology adoption by urban farmers and their impact on their welfare. In the future, we wish to provide a comprehensive analysis of the adoption of alternative agricultural technologies by both rural and urban farmers and compare them to see which factors are most effective in adopting these technologies and, which technology has more poverty-reducing effects. Furthermore, due to a lack of data, we used extension contact as a dummy variable in this study. Although it is widely used in the empirical literature, this may produce biased results to some extent. Therefore, future research should consider the number of farmer contacts during the cropping season as a variable that proxies extension contacts.

Declarations

Author contribution statement

Mesele Belay Zegeye: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Wrote the paper.

Getamesay Bekele Meshesha: Conceived and designed the experiments; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Muhammad Ibrahim Shah: Contributed reagents, materials, analysis tools or data; Wrote the paper.

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Data availability statement

Data will be made available on request.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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