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Adoption of Multiple Agricultural Technologies among Smallholder Farmers in Major Tef Growing Areas of Central Ethiopia

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Abstract

The adoption of agricultural technologies has become an important issue in the development agenda for Ethiopia, especially as a way to tackle poverty and low agricultural productivity. Using the household survey data from 240 sample respondents from Minjar Shenkora and Ada'a woredas, this study analyzes the factors that facilitate or hinder the probability and level of adoption of technologies, and intensity of technology adoption. Data were analyzed using descriptive statistics and econometric model namely, multivariate probit model, ordered probit model, and Tobit model. The model results showed that both the probability and the level of adoption of agricultural technologies are significantly affected by education level, household size, extension contacts, access to credit, farmers' confidence, farmers' membership in cooperative, farmers' perception on economic return, farmers' perception on participation in extension service provision, and the average distance to output market and extension office. The estimated result of Tobit model also indicated that education level, household size, extension contacts, access to credit, farmers' membership, and farmers' perception on economic return significantly influence the adoption and intensity of use of improved technologies. Therefore, it is crucial to engage all actors in the R&D at the various levels and promote the multiple combinations of agricultural technologies through devising possible interventions for those factors that impede the uptake of the technologies.

Keywords: Adoption; Agricultural Technology; Multivariate Probit Model; Ordered Probit Model, Tobit model; Tef

Introduction

Agriculture in Ethiopia has been playing a fundamental role in the government's policy and development strategies. The government has shown strong efforts to the promotion of improved seeds and chemical fertilizer in improving and expanding agricultural extension services (Louhichi *et al*., 2019). Since 1995 the country adopted the Participatory Demonstration and Training Extension Systems (PADETES) to promote the technological packages of improved agricultural technologies (Belay, 2003). This program mainly promotes extension packages for some selected cereals such as *tef*, wheat, maize, barley, sorghum, and millet (Misigana, 2013). The adoption of improved agricultural technologies is important to increase agricultural productivity, generate income, and reduce poverty (Louhichi *et al*., 2019; Kigali., 2012). These technologies are often suggested to be used in combination with other complimentary technologies (Spielman *et al*., 2010; Dercon *et al*., 2009; Howard *et al*., 2003), and their full potential can only be realized when technologies are used concurrently (Menale *et al*., 2018).

However, the aggregate adoption and intensity remained low and limited to only a few varieties (Regasa *et al*., 2018; Mekidelawit, 2018; Dejene and Bekele, 2015; Debelo, 2015; Negera and Getachew, 2014; Kebebew *et al*., 2013; Vandercasteelen *et al*., 2013). Although the use of improved seed and chemical fertilizer has been increasing since the country adopted the PADETES, it is still very low as compared to other developing countries (Menale *et al*., 2018; Menale *et al*., 2015; Wollni *et al*., 2010). At the national level, only 30.9% of the cultivated land was covered by the extension package program (CSA, 2018). Among the total cultivated land of *tef* crop (3.1 million ha), only 35.5% was covered by the multiple combinations of technology adoption and extension package program during 2017/18 (CSA, 2018). As a result, the agricultural productivity level of the *tef* is very low. It has been observed that huge yield gaps exist between research stations and average farmers and full package adopters and individual and non-adopters. About 70% yield gap between the research stations and farmers (Fentahun *et al*., 2017). Hence, it is a need to identify the factors that influence the adoption of agricultural technologies.

Numerous studies have been conducted to identify the factors that influence the household decision to adopt improved agricultural technologies (Deresse and Teklu, 2019; Regasa *et al*., 2018; Efa *et al*., 2016; Dejene and Bekele, 2015; Debelo, 2015; Negera and Getachew, 2014; Kebebew *et al*., 2013; Vandercasteelen *et al*., 2013). By contrast, this study differs from the previous ones in the following areas. Firstly, the combination of improved agricultural technologies in this research focuses on improved *tef* variety, chemical fertilizer, and row planting. These technologies are properly selected because farmers in the study areas are adopted and considered to be adopted. In addition, most of past studies focused on the adoption of a combination of two technologies or individually (Almaz and Begashaw, 2019; Regasa *et al*., 2018; Mekdilawit, 2018; Debelo, 2015). Secondly, the econometric models used to analyze the data were also differing. Most of them employed the multinomial logit model, Heckman's two-stage model; double hurdle model, Tobit model, and uni- and bivariate probit model (see, for instance, Deresse and Teklu, 2019; Efa *et al*., 2016; Hailu, 2008). Little is known about the combined econometric models (multivariate probit, ordered probit, and Tobit modes) allowing us to analyze the factors influencing the adoption of combinations of agricultural technologies as well as single technologies, and the variables affecting the probability of adoption may also have a different effect on the intensity of adoption. Therefore, this study will shed some light on this by investigating the factors influencing multiple agricultural technology adoption and the number of technologies adopting in which previously not much researched areas of major *tef* growing areas of Central Ethiopia.

This study analyzes the factors that influence the adoption of multiple combinations of improved *tef* variety, chemical fertilizer, and row planting. Improved *tef* variety was selected because they occupy a large share of cultivation and are a major staple food and cash crop in the study areas, as well as in the country. Hence, the objective of this study was to identify the determinants of multiple agricultural technology adoptions in major *tef* growing areas of Central Ethiopia. The study contributes to existing literature in three ways. Firstly, the study analysis includes policy-relevant variables covering major *tef* growing areas in Ethiopia. This allowed policymakers to devise appropriate interventions to overcome those that obstruct the adoption of improved agricultural technologies of *tef* growing areas. Secondly, the study extends the attention from the probability of an adoption decision to the extent of adoption as measured by the number of improved technologies adopted. Third, empirical evidence at the local level is vital since potential interventions would differ accordingly.

Materials and Methods

Description of the study areas

The survey was conducted in Minjar Shenkora *woreda* of Amhara Regional State and Ada'a *woreda* [1]of Oromia Regional State of Ethiopia. Minjar Shenkora is one of the *woredas* in the North Shewa Zone of Amhara Regional State of Central Ethiopia. The *woreda's* administrative center is Arerti and is located approximately 135 km south-east of Addis Ababa. It is bordered in the North by Hagere Maryam and Berehet *woredas*, in the South by Boset *woreda*, in the West by Gimbichu and Lume, and in the East by Fentale in the Region of Oromia. A total of 30 *kebeles*, 27 rural kebeles, and the remaining urban kebeles make up the *woreda*. The *woreda* extended astronomically between 8^{0}42'46'' N and 9^{0}7'37'' N latitudes and from 39^{0}12'57'' E to 39^{0}46'53'' E longitudes (Minjar Shenkora *Woreda* Agriculture Office (MSWAO), 2017)). It covers an area of 1,509.93 square kilometers. *Tef*, wheat, sorghum, and maize are among cereal crops and chickpea, and lentil among pulses grown in the study area. The study area is composed of three agro-climatic zones; *Dega*, *Weina Dega, and Kolla*. According to MSWAO (2017), the *woreda* has the mean annual maximum temperature varies

[1] *Woreda* is an administrative division equivalent to a district, and it represents the third level of administrative divisions in Ethiopia, following regions and zones.

from 27 to 29^0c and the mean annual minimum temperature varies from 10 to 13^0c. Minjar Shenkora is the most populated area in the North Shewa zone of the Amhara Regional State, with a total population of 171,759 people, according to the 2024 population estimates from the Ethiopian Statistical Service (ESS, 2024)).

Ada'a is one of the *woredas* in Oromia Regional State's East Shewa Zone. The administrative town of the *woreda* is Bishoftu, located 45 km east of Addis Ababa. Ada'a is bordered by Dugda Bora to the south, Akaki to the northwest, Gimbichu to the northeast, and Lome to the east. The *woreda* extended astronomically between $8^0$34’59.99’’ N latitude and $38^0$54’59.99’’ E longitude. Ada’a is an area of mixed farming activity, crop production, and livestock production. The area has two cropping seasons: *belg*[2] short rainy season extends from March to April and *meher* (main rainy season) from June to September. Crops grown in the *woreda* are *tef*, wheat, barley, maize sorghum, chickpea, horse bean, groundnut, root crops, and vegetables (Ada’a *Woreda* Agriculture Office (AWAO), 2017)). The population of Ada’a woreda is estimated to be 188,181 people according to the ESS (2024) data.

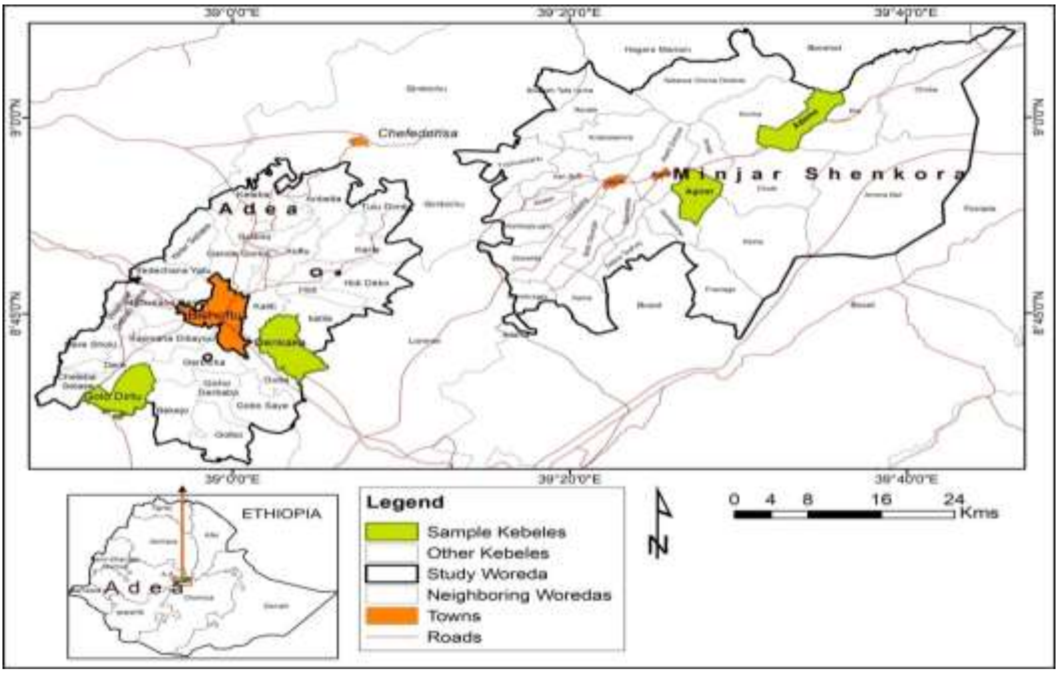

Figure 1.1 Location maps of Minjar Shenkora and Ada’a *woredas*
Source: EIAR

[2] The *Belg* season in Ethiopia is characterized as a short rainy season that typically occurs from February to May.

Sampling techniques, sample size determination

A multi-stage sampling procedure was employed to select *kebeles* from each *woredas* and randomly select households from each *kebeles*. In the first stage, based on their *tef* production potential, two *woredas* from the two regions were selected. Thus, Minjar Shenkora *woreda* from the North Shewa Zone of Amhara Regional State and Ada'a *woreda* from the East Shewa Zone of Oromia Regional State were purposely selected. In the second stage, four *kebeles* (two from each *woreda*) were randomly selected for this study. Hence, Agirate and Adama *kebeles* from Minjar Shenkora *woreda* and Denkaka and Golo-Dertu *kebeles* from Ada'a were randomly selected. In the third stage, the proportional random sampling method was applied to determine the sample size in each *kebele*. Representative households from each sample *kebeles* were determined by using a formula suggested by Yamane (1967). This simplified formula required sample size at 95% confidence level, degree of variability = 0.5, and level of precision = 5%. Finally, 240 farm households were randomly selected for face-to-face interviews by using a simple random sampling method.

$$n = \frac{N}{1+N\,(e^2)} \quad \text{.............................} \quad (1)$$

Where n = sample size; N = population size; e = margin of error

The study used the household survey data through randomly selected farm households in Minjar Shenkora and Ada'a *woredas*. A structured questionnaire was prepared, and the sample respondents were interviewed by well-trained and experienced enumerators who have well- known the study areas and the local languages under close supervision. The questionnaire comprised of detailed items about farm households' data including demographic characteristics, resource endowments, institutional factors, extension and market services, extension office, input and output market access, and farmers' perception about economic return, package appropriateness, and participation in extension service provision process. Moreover, secondary data sources used to compile the background information of the study, establish the conceptual and econometric framework to select models and methods of estimations. Sources of secondary data were related literature which comprised of published books, peer-reviewed articles, research reports, and published and unpublished documents.

Econometric framework and estimation strategies

Farmers are supposed to be rational economic agents who maximize utility (Chilot *et al.*, 2015). The decision to adopt improved agricultural technologies is made when the perceived utility from using combinations of technologies is significantly superior to what would be the case with individual technology or without the technology. Farmers utilize a mix of technologies to address a wide range of agricultural production challenges, therefore the decision to adopt is essentially multivariate (Hailemariam, 2012). Attempting univariate modeling, according to Dorfman (1996), would not incorporate useful economic information concerning interdependent and simultaneous adoption decisions. Moreover, independent modeling of the multiple adoption decision of households could ignore the potential association among the unobserved disturbances in the decision equations, as well as the use of the multiple technologies. As a result, the multivariate probit (MVP) econometric model was used in this study, which predicts the influence of the set of explanatory variables on each of the technologies while allowing unobserved and/or unmeasured factors (error terms) to be freely associated (Lin *et al*., 2005).

The model estimates from the multivariate specification improve over those from univariate specifications when the error correlations are significantly different from zero. The univariate model has the following limitations including lack of relationship analysis, limited predictive power, and overlooking interactions. In the MVP model estimated here, the choice of improved varieties related to each of the improved technologies corresponds to a binary choice (yes/no) equation and the choices are modeled jointly while accounting for the correlation among disturbances. The econometric specification of this study has two parts: (1) farmers' choice of inter-related improved technologies is modeled using a multivariate probit model (MVP); (2) we analyze the factors affecting the extent of combinations of technologies adopted, using pooled ordered probit models; (3) we analyzed the intensity of improved seed adoption using Tobit model. The MVP model solely analyzes the likelihood of adopting agricultural technologies, making no differentiation between the number of technologies adopted by farmers who adopt a single technology and those who adopt a combination of multiple technologies (Hiwot *et al*., 2016; Hailemariam *et al*., 2013). Thus, to fill this gap the ordered probit model is used to analyze the determinants of the adoption of a combination of technologies.

A multivariate probit (MVP) model

In a single-equation model, information on a farmer's adoption of one technology does not alter the likelihood of adopting another technology. However, the MVP approach models the impact of a set of independent factors on each of the different improved technologies at the same time, while allowing for the potential correlation between unobserved disturbances and the adoption of different technologies (Belderbos *et al*., 2004). The observed outcome of alternative technology adoption can be modeled following a random utility formulation. Consider the i^{th} farm household (i= 1,..., N) that must decide whether to adopt or reject a particular combination of technology. Let U_0 represent the farm household that uses local and traditional practices, and U_A denotes the benefit of adopting A^{th} improved technologies: where A denotes choice of improved tef variety (V), Chemical fertilizer (F), and row planting practice (R). The farm household decided to adopt A^{th} technologies if $Y^*_{im} = U_A - U_0 > 0$. Y^*_{im} is a latent variable determined by observed household, and location characteristics (X_{im}) and unobserved characteristics (ε_{im}). According to Greene (2012), the model specifies as:

$$Y^*_{imA} = \beta_A X_i + \varepsilon_{im}, (A = V, F, R) \qquad (2)$$

By using the indicator function, the unobserved preferences in equation (2) convert into the observed binary outcome equation for each choice as follows:

$$Y^*_{imA} = \begin{cases} 1 & if\, Y_{imA} > 0 \\ 0 & otherwise \end{cases} \quad (A = V, F, R) \qquad (3)$$

In the multivariate model, the error terms jointly follow a multivariate normal distribution (MVN) with zero conditional mean and variance normalized to unity where: $(u_V, u_F, u_R) \sim MVN(0, \eta)$ and the symmetric covariance matrix η is given by:

$$\eta = \begin{bmatrix} 1 & \rho_{VF} & \rho_{VR} \\ \rho_{FV} & 1 & \rho_{FR} \\ \rho_{RV} & \rho_{RF} & 1 \end{bmatrix} \qquad (4)$$

The covariance matrix's off-diagonal entries represent the unobserved correlation between the stochastic components of the various improved technologies. According to this hypothesis, equation (4) generates an MVP model that jointly depicts decisions to adopt a specific technology. This specification with non-zero off-diagonal elements enable correlation across the error terms of numerous latent equations, which represent unobserved characteristics influencing the choice of various improved technologies (Hiwot *et al*., 2016).

Ordered probit model

The MVP model described above only considers the probability of technology adoption, with no distinction made between the numbers of technologies adopted, such as farmers who adopt one technology versus those that use a combination of multiple technologies (Hailemariam *et al*., 2013). The ordered probit is used to fill this gap by analyzing the factors that influence the adoption of a combination of technologies. While adoption of a combination of improved technologies, defining a cut-off point between technology adopters and non-adopters is the main problem in identifying the factors influencing the level of adoption of improved technologies. In this study, several households were not adopting the whole package; some households use a combination of some technologies on their plots but not others. Consequently, for multiple combination adoption, it is difficult to quantify the extent of adoption is usually done in adoption literature. To overwhelm this problem, this study uses the number of improved technologies adopted as our dependent variable measuring the extent of adoption.

The number of technologies adopted may have been treated as a count variable; count data is typically investigated using a Poisson regression model, but the underlying assumption is that all occurrences have the same probability of occurrence. Nonetheless, the fundamental assumption of Poisson regression, that all events have an equal probability of occurrence, is disrupted because the probability of adopting the first technology may differ from the probability of adopting a second or third, given that farm households have already gained some experience with technology adoption in the latter case. The number of technologies used by farm households is then used as an ordinal variable in the estimation, with an ordered probit model.

Assume that the latent random variable y_i* is dependent and use y_i as a stand-in for it as well as an observed variable with "j" response categories. The probit model is defined as follows:

$$y_i* = x^*\beta + \varepsilon_i,\ i=1,2,3,\ldots \quad (5)$$

y_i* is the hypothesized predicators of HDD, βs is a vector of parameters to be estimated and ε_i is an error term that is assumed to be normally distributed. Then, the values for the observed variable y_i are assumed to be related to the latent variable y_i* in the following manner:

$$y=j,\ \text{if}\ \mu_{j-1} < y_i^* \leq j=1,2,3,\ldots,N \quad (6)$$

where μ refers to the unknown threshold parameters, u - i= -∞, u_o= 0, u_j = ∞ and the estimated cut-off points, μ follows the order μ -1 i< $\mu_0 < \mu_1$ …….. < μ_j. The probabilities that a given household will fall within a response category of j follows:

$$t_{ij} = t(y_i = j) = t(u_{j-1} < y_i^* \leq u_j) = R(u_j - x_i'\beta) - R(u_{j-1} - x_i') \quad (7)$$

where R′(·) is the standard normal cumulative distribution function and j is the response categories, in this case 1, 2 and 3 since there are three categories for HDD.

Table 1 The number of improved technology packages used by farm households

Technology Packages	Category	Improved *Tef* Variety (V)		Chemical Fertilizer (F)		Row Planting (R)		%
		V_o	V_1	F_o	F_1	R_o	R_1	
$V_o F_o R_o$	Non-adopters	√		√		√		8.8
$V_1 F_o R_o$	Individual technology adopters		√	√		√		10.0
$V_o F_1 R_o$		√			√	√		17.1
$V_o F_o R_1$		√		√			√	8.3
$V_1 F_1 R_o$	Combination technology adopters		√		√	√		13.8
$V_1 F_o R_1$			√	√			√	7.5
$V_o F_1 R_1$		√			√		√	12.5
$V_1 F_1 R_1$	All three technologies adopters		√		√		√	22.1
Total								**100.0**

Note: V, F and R refer to technology set for improved *tef* variety, chemical fertilizer and row planting practice, respectively; subscript '0' denotes non-adoption, while '1' denotes adoption of technologies

Tobit model

The bulk of adoption studies used dichotomous regression models, which only explain the likelihood of adoption versus non-adoption and not the extent and intensity of adoption. However, Tobit model is more appropriate to deliver reliable output of both discrete and continuous variables (McDonaled and Moffit, 1980) as it measures the probability of adoption and the level of use of the technology. This model was chosen because, unlike other adoption models such as logistic and probit, it indicates both the probability of new technology adoption and the intensity of its use. The Tobit model is a statistical method used to analyze censored dependent variables, which are common in situations where the outcome variable is not fully observed. In the context of measuring the intensity of improved technology use, this model can be particularly useful when the data on technology usage is limited by a threshold. The model can be expressed mathematically as follows:

$Y_i = \beta_i X_i + u_i$, i= 0, 1, 2,…, n; if $\beta_i X_i + u_i > 0$ or $\beta_i X_i + u_i = 0$ otherwise …(8)

Where, Y_i = the observed dependent variable (improved *tef* varieties); X_i = explanatory variables; β_i= a KXi matrix of parameters to be estimated; U_i = independently and normally distributed error term with mean zero and constant variance Ui~N(0, 1).

The maximum likelihood method was used to calculate the model's parameters. Following Tobin (1958), the expected value of adoption and level of Tef improved varieties adoption will be estimated using the following formula:

$E(Y_i) = X\beta F(z) + \delta f(z)$ …………………………………………….. (9)

Where, $z = X\beta/\sigma$; F (z) is the cumulative distribution function; f (z) is the value of derivative of the normal curve at a given point; z is the Z-score for the area under normal curve; β is a vector of Tobit maximum likelihood estimates and σ is the standard error of the error term.

According to Madalla (1983), the adjusted estimates are the marginal effects of explanatory variables on the expected value of the dependent variable and given by:

$$\frac{\partial E\,(Yi)}{\partial X_i} = F\,(z)\,\beta_i \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \;(10)$$

The change in the probability of area under *tef* varieties as independent variable X_i change is given by:

$$\frac{\partial F\,(z)}{\partial X_i} = f\,(z)\,\frac{(\beta i\,)}{\sigma} \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \;(11)$$

And the change in the level of adoption with respect to a change in an explanatory variable among technology adopters is:

$$\frac{\partial E\,(Yi/Y{*}>0)}{\partial X_i} = \beta\,[1 - z\,\frac{f(z)}{F(z)} - (\frac{f(z)}{F(z)})2] \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \;(12)$$

Description of dependent and explanation of variables

Table 2. Definitions and summary statistics of the variables used in the analysis

Variables	Description of variables	Mean	STD
Dependent variables			
V	1= if the household adopted improved *tef* variety	0.53	
F	1= if the household adopted chemical fertilizer	0.66	
R	1= if the household adopted row planting	0.50	
Explanatory variables			
Demographic characteristics			
SEX (+)	1= if the household head is male	0.90	
AGE (-)	Age of the household head in years	45.45	12.54
EDUC_0 (+)	1= if the household head has no formal school	0.52	
EDUC_1 (+)	1= if the household head between 1 and 8 grade	0.45	
EDUC_2 (+)	1= if the household head greater than 8 grade	0.03	
HH_SIZE (+)	Number of household size in ADE	4.71	1.92
Resource endowments			
FARM_SIZE (+/-)	Farm size in ha	2.75	1.89
LIVESTOCK (+)	Livestock herd in TLU	5.75	4.15
OFF_FARM (-)	1= if household engaged in off farm activities	0.16	
Institutional factors			
CREDIT (+)	1= if the household access credit	0.56	
COOPERATIVE (+)	1= if the household member of cooperatives	0.70	
Extension services			
CONTACT (+)	Frequency of DA contacts with farmers	3.30	6.70
CONFIDENT (+)	1 = if the household is confident with the skills of DA	0.54	
TRAINING (+)	1= if the household access to training	0.70	
DIS_EXT (-)	Distance to the nearest extension office (km)	4.14	3.58
Market access			
DIS_INPUT (-)	Distance to the nearest input market (km)	4.74	4.36
DIS_OUTPUT (-)	Distance to the nearest output market (km)	10.18	6.94
Farmers perception (1-5 scale)			
ECO_RETURN (+)	Farmers' perception on the economic return	3.78	0.94
PACKAGE (+)	Farmers' perception to packages appropriateness	2.85	1.35
PARTICIPATION (+)	Farmers' perception on participatory of extension service	2.24	0.83
Woredas dummy			
MINJAR	1= if the household in Minjar Shenkora *woreda*	0.50	
ADAA	1= if the household in Ada'a *woreda*	0.50	

Source: Own calculation based on field survey

Results and Discussion

Characteristics of sample farm households

Table 2 presents summary statistics for the variables utilized in econometric analysis. The means and standard deviations of farm household characteristics, resource endowments, extension service, market access, and farmers' perception of the sample households were calculated. The mean age of the sample household is 45.5 (±12.5) years. The majority of farm households in the study areas are male headed (90%). The average household size of the sample respondents is 4.7 (±1.9) with adult equivalent (ADE). The results also show that 52% of the household heads had no formal education while 45% and 3% were educated up to grade 8 and above grade 8, respectively.

As far as the household asset endowments are concerned, the average cultivated land size of the sample households is 2.75 (±1.9) ha, and the households have on average 5.8 TLU. Besides, only 16% of farm households engaged in off-farm activities. Regarding institutional variables, 70% of farm households are members of agricultural cooperatives, about 56% of farm households had access to credit. Almost all farm households get extension services though the frequency differs. The survey result indicates that the average number of contacts paid by DAs is 3.3 (±6.7) times. Yet, about 54% of farm households are confident with the skill of DAs. Among those sample respondents, 70% are access training for the last two years in the study areas.

Concerning farmers' perceptions, the survey results show that the positive perception of farmers on the economic return from adopting improved technologies is 3.8. Moreover, the perception of farm households on the appropriateness of the extension packages on average is 2.9. This implies most of the farmers' perception of the extension packages' appropriateness is at an average level. Besides, the perception of farmers on the participatory nature of the extension delivery system is below the average levels, which are 2.2.

Joint probabilities of improved agricultural technology adoption

The probability distribution of the joint adoption of improved *tef* varieties, chemical fertilizer, and row planting practices is presented in Table 3. Of the total eight combinations of improved technologies, the combinations of technologies that involve improved *tef* varieties account for 53.4%. However, all three technologies were adopted by 22.1% of the sample households, while only 10% adopted improved *tef* varieties. Farm households jointly adopting improved *tef* variety and chemical fertilizer, constitute 13.8% while 7.5% of farm households adopted improved *tef* variety and row planting simultaneously. The joint probability of using simultaneous technologies adoption of all three improved technologies is minimal (22.1%), suggesting a lot needs to be done in popularization, demonstrating, and creating better access to combinations of technology packages for farm households. Chemical fertilizer was the most common improved agricultural technologies adopted by the sample respondents in the study areas. Similarly, households, who adopt the combinations of improved technologies involving chemical fertilizer constitute 65.9%. As an individual technology, fertilizer was adopted by 17% of households, in combination with improved variety by 14% of households, and in combination with row planting and improved variety by 22.1%. Row planting alone was adopted by only 8.3% of households, in combination with improved variety by 7.5% of the households.

About 9% of the respondents benefited from none of the three improved technologies.

Table 3. Joint probability of adoption of improved technologies (%)

Percent adopting in	Technology package	Joint probability
All three technologies	$V_1 F_1 R_1$	22.1
Improved *tef* variety and chemical fertilizer	$V_1 F_1 R_o$	13.8
Improved *tef* variety and row planting	$V_1 F_o R_1$	7.5
Chemical fertilizer and row planting	$V_o F_1 R_1$	12.5
Only improved *tef* variety	$V_1 F_o R_o$	10.0
Only chemical fertilizer	$V_o F_1 R_o$	17.1
Only row planting	$V_o F_o R_1$	8.3
Non-adoption	$V_o F_o R_o$	8.8

Source: Own calculation based on field survey

Note: V, F and R refer to technology set for improved variety, chemical fertilizer and row planting, respectively; subscript '0' denotes non-adoption, while '1' denotes adoption of technology packages.

Conditional and unconditional adoption probabilities

Table 4 presents the unconditional and conditional probabilities of the adoption of technologies. The simulated maximum likelihood (SML) estimation result shows that the likelihood of farm households adopting improved *tef* variety, chemical fertilizer, and row planting were 53.4%, 65.0%, and 50.0% respectively. The conditional probability of adopting improved technologies and practices or a combination of technologies and practices, however, is generally greater telling the existence of synergy. The unconditional probability of adopting chemical fertilizer is 65%. This increases to 69% and 77% conditional on the adoption of one technology (improved *tef* variety) and two technologies (improved *tef* variety and row planting practices), respectively. However, the conditional probability of adopting chemical fertilizer is no significant difference on the farm when farmers adopt only improved *tef* variety (67%).

Table 4. Conditional and unconditional probabilities of adoption of technologies

	Improved *tef* Variety	Chemical Fertilizer	Row Planting Practice
$P(Y_i = 1)$	0.53	0.66	0.50
$P(Y_i = 1 \mid Y_v = 1)$	1.00	0.69	0.52
$P(Y_i = 1 \mid Y_F = 1)$	0.57	1.00	0.50
$P(Y_i = 1 \mid Y_R = 1)$	0.52	0.67	1.00
$P(Y_i = 1 \mid Y_v = 1, Y_F = 1)$	1.00	1.00	0.54
$P(Y_i = 1 \mid Y_v = 1, Y_R = 1)$	1.00	0.77	1.00
$P(Y_i = 1 \mid Y_F = 1, Y_R = 1)$	0.61	1.00	1.00
$P(Y_i = 1 \mid Y_v = 1, Y_F = 1, Y_R = 1,)$	1.00	1.00	1.00

Source: Own calculation based on field survey

Note: Y_i is a binary variable representing the adoption status with respect to improved technologies i (V = improved *tef* seed, chemical fertilizer (F), and row planting practice (R)

Factors affecting households' adoption decision: A MVP model results

Model specification test

While using MVP model, relevant pre and post estimation tests were performed. The MVP model estimate of the simulation results for farmer's technology adoption decisions is presented in Table 5. Although farmers adopt a combination of improved technologies, there are significant factors that could influence their decision to choose a particular technology. This section has identified those variables using MVP model estimates. The Wald test [2 (75) = 197.40, p = 0.000] rejects the hypothesis that all regression coefficients in each equation are jointly equal to zero since the model fits the data reasonably well. The Wald test rejects the hypothesis that all coefficients in each equation are jointly equal to zero, implying that the variables in the model explain a significant amount of the variability in the dependent variables. The model estimates differ considerably across the equations, representing the appropriateness of differentiating between technologies. This was also formally tested by estimating a constrained specification with all slope coefficients forced to be equal. Furthermore, the likelihood ratio test of the null hypothesis that the covariance of the error terms across equations is uncorrelated is rejected. It reflects the heterogeneity in the adoption of technologies and, subsequently, supports a separate analysis of each rather than aggregating them as a single dependent variable.

Determinants of farmers' adoption of Tef technologies

Education was found to affect the adoption of tef technologies positively and significantly. The result showed that formal education of the household head up to grade 8 has a positive and significant effect on the household decision to use row planting practice. Education improves decision-making locative ability by teaching farmers to think and use information sources effectively. Higher education is believed to be associated with the ability to collect process and utilize new information suggesting households with higher levels of education would be highly likely to use new practices and adopt the technologies. The finding is similar to the results of Deresse and Teklu (2019); Dejene and Bekele (2015); Negera and Getachew (2014) who reported that there was a positive and significant association between education level and technology adoption.

Household size has also a significant and positive effect on the household decision of *tef* row planting practice. It is normally associated with higher family labor that would enable a household to accomplish various agricultural tasks timely. This may be due to farm households with more labor force could practice row planting than households with smaller family size on *tef* production. Most Ethiopian farmers have not used labor-saving technologies like tractors, harvesters in their production system; hence, household size critically influences the household decision to adopt new technologies. This result is in line with Deresse and Teklu (2019); Mekidelawit (2018); Dejene and Bekele (2015); Hassen *et al*. (2012).

The frequency of extension contacts has a positive and significant effect on the adoption of improved *tef* variety, chemical fertilizer, and using row planting practices. This is mainly because extension service is a necessary catalyst to adopt improved technologies as they are the major source of agricultural information. Likewise, farm households with confidence with the skills of DAs have more probability of adopting chemical fertilizer and row planting than those households with smaller or no confidence in the skills of DAs. This may be due to those DAs who have technical skills easily demonstrated and convinced households to adopt new technologies and innovations. The probability of adopting improved *tef* variety and chemical fertilizer is affected by households' membership in agricultural cooperatives and access to rural finance (credit). With limited or insufficient information sources and imperfect markets, social networks such as farmer cooperatives increase information exchange and provide farmers with access to new technology and credit. This finding suggests that to improve the adoption of *tef* technology, agricultural cooperatives, and rural service providers need to be supported because they can effectively help farmers in providing credit, agricultural inputs, information, and stable market outlets. This result is in line with Hailemariam (2012) and Mekidelawit (2018).

Distance to the nearby extension office, distance to input and output market is negatively influenced by the adoption of improved *tef* technologies. An increase in distance to the extension office, input and output markets prevent households getting relevant and timely information for purchasing agricultural inputs and selling their outputs. Distance to the input market has a negative and significant impact on the adoption of improved *tef* variety, reflecting transaction and access costs. Similarly, the distance from the output market has a large and negative impact on the use of chemical fertilizer and row planting practices. Perception of farming households on the economic return has a positive impact on the adoption of improved *tef* variety, chemical fertilizer, and row planting practices at 1%, 1%, and 5% significance level, respectively. This implies that the higher the economic return from using improved *tef* variety, chemical fertilizer, and row planting the greater likelihood of farmers motivates us to adopt multiple combinations of *tef* technologies.

Table 5 Multivariate probit estimation results for improved technology adoption decisions

Explanatory variables	Improved *tef* variety		Chemical fertilizer		Row planting practice	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
SEX	0.2551	0.3183	0.0628	0.3312	-0.0792	0.3259
AGE	-0.0015	0.0078	0.0099	0.0083	-0.0066	0.0076
EDUC_0	0.2977	0.5739	0.6162	0.5284	0.0427	0.5578
EDUC_1	0.3554	0.5734	0.2215	0.5252	0.7493*	0.5564
HH_SIZE	0.0186	0.0514	0.0297	0.0532	0.0961**	0.0498
LIVESTOCK	0.0249	0.0272	0.0436	0.0299	0.0268	0.0268
FARM_SIZE	0.0354	0.0622	0.0243	0.0613	0.0464	0.1649
COOPERATIVES	0.7789***	0.2274	0.5146***	0.2218	0.6229***	0.2193
CREDIT	0.5504**	0.2249	0.2299*	0.2212	0.1991	0.2100
OFF_FARM	0.1769	0.2595	0.2305	0.2765	0.1172	0.2591
CONTACT	0.0788***	0.0323	0.0601*	0.0367	0.0166*	0.0191
TRAINING	0.0260	0.2260	-0.1206	0.2331	-0.0953	0.2213
CONFIDENT	0.2531	0.2520	0.4731*	0.2642	0.4357**	0.2437
DIS_EXT	-0.0312	0.0417	-0.0805**	0.0418	-0.0789**	0.0401
DIS_INPUT	-0.0355*	0.0356	-0.0271	0.0347	0.0243	0.0335
DIS_OUTPUT	-0.0074	0.0158	-0.0750***	0.0198	-0.0322**	0.0158
ECO_RETURN	0.2842***	0.1174	0.0480***	0.1685	0.0926**	0.1084
PACKAGE	0.0907	0.0790	0.0031	0.0823	0.0005	0.0769
PARTICIPATORY	0.1456	0.1316	0.3014	0.1365	0.0328	0.1301
MINJAR	0.3840	0.7103	0.0673	0.6127	0.7008	0.7215
ADAA	0.2905	0.7144	0.5204	0.6216	0.6392	0.7314
cons	-1.0527	1.6434	-2.3488	1.4914	0.0390	1.6809
Wald chi^2 (75) = 197.40	Prob > chi^2 = 0.0000					
No of Observation = 240						

Source: Own estimation based on field survey
Note: *, **, and *** denotes significance level at 10%, 5%, and 1%

Number of technologies adopted: Ordered probit model results

Table 6 shows the number of improved technologies adopted by sample households. The number of improved agricultural technologies adopted by farmers from the combination is the model's dependent variable. Approximately 91% of farming households have implemented at least one of the improved technologies, with about 34% adopting two. The descriptive statistics for a variety of technologies utilized along the probability predicted by the ordered probit model are shown in Table 6.

Table 6 Percentages of improved technologies adoption by sample farm households

Number of Technologies	Percent
(0) Non-adoption	8.8
(1) Adoption of single technology	35.4
(2) Adoption of a combination of two technologies	33.8
(3) Adopted of a combination of three technologies	22.1

Source: Own calculation based on field survey

Table 7 shows the results from pooled and marginal effects ordered probit models. The chi-squared statistic for the ordered probit model is (Wald chi2 (19) = 119.34, P = 0.0000) and is statistically significant, indicating that the joint test of all slope coefficients equal to zero is rejected. The ordered probit model results reveal the number of technologies adopted is positively associated with educational level, livestock ownership, farm size, cooperatives membership, credit access, frequency of DAs contacts, training, farmers' confidence with skills of DA, and perception of farmers on econometric return. Meanwhile it is negatively associated with the distance to the extension office and the market from homestead.

Education increases human capital and contributes positively to change farmer's attitudes and determines the readiness to accept new ideas and innovations (Hiwot *et al*., 2016). As in the adoption decision, the results revealed that education level up to grade 8 has a positive and significant effect on the level and number of adoptions of improved agricultural technologies. Each extra year of schooling for the household head increases the likelihood of adopting two technologies by about 18.4%. Household assets (such as cattle ownership) have a beneficial impact on the adoption of two or more improved technologies. A one-unit increase in livestock ownership measured in TLU increases the likelihood of adopting two and three technologies by 0.4% and 0.5%, respectively.

Having large farmland contributes to perceived security and increased willingness to invest in new technologies and practices. The farm size has a significant and positive effect on the level of technology adoption. A one-unit increase in farmland could increase the probability of adoption of two and three improved technologies by 4.1% ($P<0.05$) and 0.3% ($P<0.1$), respectively. Social capital variables such as farmers' membership of agricultural cooperatives have significant and positive effects on the number of improved technologies adopted, with varying marginal probabilities. Farmers who are members of agricultural cooperatives could easily access agricultural information and new technologies. If a household is a member of agricultural cooperatives, the probability of adopting two and three technologies increases by 22.1% and about 11%, respectively. Access to credit also has a positive and significant influence on household decisions to adopt improved technologies (Legesse *et al*., 2001; Tesfaye, 2001). Farm households who access financial services (credit) would increase the probability of adopting a combination of three technologies by 0.3% signifying that households who immediate access to money (those who need it) are more likely to purchase agricultural inputs.

Households' contacts with DAs increase the probability of getting new agricultural information, technologies, and innovations. If the frequency of contacts increases by one unit, the probability of adopting three technologies increases by 1.3%. This implies that timely and adequate provision of agricultural information would influence the mindset of the farm households positively. Similarly, farmers who have confidence with the skills of DAs have more probability of adopting three technologies by about 10% than those households with smaller or no confidence with the skills of DAs on *tef* production. Training has a positive and significant effect on the number of improved technology adoption. Farmers who received awareness creation and capacity-building training are more likely to adopt a combination of various technologies. The marginal effect analysis revealed that farm households who access training would increase the probability of adopting three agricultural technologies by 4.1% ($P<0.1$).

The perception of farmers on economic returns has a positive and significant influence on the adoption of a combination of improved technologies. A one birr increases in the economic benefits would have the effect of increasing the chances of adopting a combination of two and three improved technologies by about 7% ($P<0.05$) and 10% ($P<0.01$), respectively. Distance to the nearby extension office and output market significant and negative impact on the number of improved tef technologies adopted. Farmers who do not have their means of transportation or access to public transport to the extension office and output market are 1.3% and 0.7% less likely to adopt three technologies, respectively.

Table 7 Ordered probit model estimates for the number of improved technologies adopted

Variables	Pooled ordered probit model		Marginal effects							
			Prob (Y= 0│X)		Prob (Y= 1│X)		Prob (Y= 2│X)		Prob (Y= 3│X)	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
SEX	0.411	0.251	0.156	0.024	-0.233	0.074	0.051	0.112	0.025	0.033
AGE	-0.003	0.006	-0.007	0.015	-0.004	0.003	0.003	0.002	0.000	0.001
EDUC_0	0.392	0.426	0.617	0.193	0.057	0.192	0.141	0.182	0.028	0.102
EDUC_1	0.115**	0.0421	0.719	0.828	0.041	0.190	0.184*	0.175	0.076	0.126
HH_SIZE	0.002	0.040	0.004	0.0793	0.009	0.018	0.005	0.017	0.003	0.007
LIVESTOCK	0.022*	0.021	0.006	0.012	0.004	0.009	0.004*	0.009	0.005*	0.004
FARM_SIZE	0.019*	0.046	0.007	0.126	0.015	0.022	0.041**	0.019	0.003*	0.008
COOPERAT.	0.991***	0.186	0.085***	1.341	0.256***	0.081	0.221***	0.064	0.108***	0.037
CREDIT	0.105**	0.167	0.048**	0.850	0.131*	0.072	0.012	0.071	0.003*	0.029
OFF_FARM	0.119	0.206	0.009	0.029	0.031	0.086	0.037	0.091	0.039	0.055
CONTACTS	0.056**	0.026	0.003	0.006	0.018	0.011	0.004	0.007	0.013**	0.006
TRAINING	0.033*	0.183	0.011	0.201	0.077	0.078	0.069	0.079	0.041*	0.038
CONFIDENT	0.319**	0.164	0.013	0.242	0.090	0.070	0.076	0.069	0.098**	0.042
DIS_EXT	-0.103***	0.033	-0.004	0.073	-0.036**	0.016	0.016	0.014	-0.013*	0.007
DIS_INPUT	0.016	0.027	0.001	0.021	0.018	0.014	-0.016	0.012	0.002	0.005
DIS_OUTPUT	-0.031**	0.012	-0.005	0.010	0.011*	0.006	0.004	0.005	-0.007***	0.003
ECO_RETURN	0.303***	0.087	0.009	0.167	0.033	0.037	0.069*	0.038	0.100***	0.032
PACKAGE	0.091	0.062	0.046	0.087	0.010	0.027	0.015	0.027	0.014	0.011
PARTICIP.	0.060	0.104	0.009	0.187	0.003	0.045	0.087*	0.046	0.008	0.017
/cut1	0.043	0.682								
/cut2	1.641**	0.689								
/cut3	2.879***	0.701								

Source: Own calculation based on field survey
Note: *, **, and *** denotes significance level at 10%, 5%, and 1%, respectively

Intensity of improved technology adoption

The result of the Tobit model indicated that the level of education of the head of the farming household has a positive and significant influence on the adoption and use of improved technologies with each additional year of schooling increasing the probability of adoption by 9.3% (Table 8). Education enhances farmers' ability to acquire, analyze, interpret and use information relevant to the adoption of agricultural innovations. This suggests that farmers with higher educational backgrounds would have better opportunities to access information and can easily understand the benefit of improved *tef* technology and apply as per the recommendation. This result is in line with Hiwot *et al*. (2016); Alene *et al*. (2000) who reported positive and significant influence of household heads' educational level on adoption and intensity of use of improved technology packages.

Household size has a positive and significant influence on the number of hectares of land planted to improved *tef* variety. Each extra person in a household makes it 1.8% more likely that the household will adopt technologies. Furthermore, on average, each additional family size has increased the number of hectares of farmland planted to improved *tef* variety by 2.9% for the whole sample of study and by 1.3% for technology adopters. The probability of adoption and intensity of improved *tef* seed is positively and significantly influenced by a household's membership in agricultural cooperatives. Farming households' membership in agricultural cooperatives can increase the probability of adoption by 30.6%. Farming households who are members in agricultural cooperative can increase the use of improved *tef* variety by 29.8% for the whole sample study, and by 51.3% for users.

Extension service increases the probability of getting new agricultural information, technologies, and innovations. It measured in the number of visits per year by the DA to a farmer during the cropping season. As indicated in Table 8, the number of contacts with the farmers has a positive and significant influence on the adoption and intensity of use of improved *tef* variety. Each additional contact by the DA to a farmer increased the probability of adoption by 3.1%. On average, each additional visit has also increased the number of hectares of land planted with improved *tef* variety by 3% for the entire sample and by 0.9% for users. The perception of economic return from adoption is another important factor which influences farmers' decision to adopt improved varieties as it enables farmers to acquire seeds and other inputs at the right time. It has a positive and significant influence on the adoption and intensity of adoption of improved *tef* variety. A one birr increases in the economic return would have increased the probability of adopting improved seed by 12.3%. Each additional economic return has also increased the number of hectares of land covered with improved *tef* variety by 9.8% for the entire sample and by 15% for adopters.

Table 8 Tobit model results of the adoption and intensity of use of improved technologies

Explanatory Variables			Marginal effect					
			Change in probability of adoption		Change in intensity of adoption		Total change	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
SEX	0.277	0.194	-0.152	0.124	0.197	0.183	0.101	0.120
AGE	-0.003	0.004	0.002	0.003	-0.006	0.004	-0.003	0.002
EDUC_1	0.239**	0.126	0.110	0.228	0.003	0.273	0.093	0.194
EDUC_2	0.240	0.323	0.132	0.223	0.005	0.267	0.076	0.191
HH_SIZE	0.041*	0.029	0.018	0.020	0.027	0.029	0.013	0.019
LIVESTOCK	0.011	0.015	0.011	0.015	0.009	0.015	0.009	0.011
FARM_SIZE	0.023	0.033	0.016	0.024	0.023	0.033	0.016	0.024
COOPERATIVE	0.531***	0.140	0.306	0.084	0.513	0.138	0.298	0.084
CREDIT	0.243**	0.122	0.193	0.082	-0.263	0.120	-0.207	0.080
OFF_FARM	0.046	0.157	0.025	0.103	-0.041	0.156	-0.018	0.102
CONTACT	0.048***	0.008	0.031	0.014	0.009	0.008	0.030	0.014
TRAINING	0.089	0.133	0.012	0.094	0.093	0.132	0.018	0.092
CONFIDENT	0.093	0.122	0.045	0.081	0.072	0.121	0.031	0.080
DIS__EXT	-0.019	0.023	0.015	0.016	-0.024	0.023	-0.018	0.016
DIS_INPUT	0.015	0.020	-0.013	0.014	0.014	0.019	0.012	0.014
DIS_OUTPUT	-0.005	0.009	0.005	0.006	-0.005	0.008	-0.005	0.006
ECO_RETURN	0.187***	0.066	0.123	0.045	0.150	0.060	0.098	0.041
PACKAGE	0.069	0.044	0.055	0.031	-0.075	0.044	-0.058	0.031
PARTICIP	-0.072	0.076	0.053	0.052	-0.098	0.074	-0.072	0.051
_cons	-0.758	0.526						
/sigma	0.752	0.053						

Number of Observation = 240; Pseudo R^2= 0.1127; F(19, 221)= 4.01; Prob > F= 0.0000

Source: Own estimation based on field survey

Note: *, **, and *** denotes significance level at 10%, 5%, and 1%

Conclusions and Policy Implications

This study has analyzed the adoption of multiple agricultural technologies among *tef* growing farmers using cross-sectional data collected from Central Ethiopia. The technologies considered for this study are improved *tef* variety, chemical fertilizer, and row planting practice. Using MVP and ordered probit models this study looked to analyze the factors that influence the adoption of multiple agricultural technologies, and the number of technologies adopted. The results of the MVP model revealed that education level, household size, livestock ownership, farmers' membership in an agricultural cooperative, access to credit, number of extension contacts, farmers' confidence with the skills of DAs, farmers' perception on economic return, farmers' perception on participation in the extension service delivery, average distance to output market and distance to extension office are significantly associated with the probability and the extent of adoption of agricultural technologies. Specifically, social capital and strong rural farmers' institutions, and market access are important policy variables that have a significant effect on the adoption of agricultural technologies.

Local farmers' institutions can play an important role in providing timely information, inputs, finance, insurance, and technical support in a country where there is information asymmetry for input and output markets. The study suggested the need for strengthening agricultural cooperatives and rural financial institutions and service providers to enhance multiple technology adoption. The importance of farm household assets in influencing the purchase of input calls for improving credit delivery systems. Livestock ownership influences the adoption of multiple agricultural technologies. Farming households who own more livestock holdings and access money through credit have more probability of earning money from the sale of their livestock and their products which help them to purchase various inputs. Farmers' perception of the economic return is the most important driving factor for multiple technology adoption. Hence, it forces the extension service needs to focus on demand-driven and market-oriented diversified technologies that suit the specific needs of farmers. This implies, as a household perception of expectation on the economic return is positive, the probability of using multiple technology adoption is higher. It is therefore rational to say the higher the economic return from using multiple agricultural technologies, the greater the likelihood of farmers participating in the extension system and adopting multiple agricultural technologies.

In conclusion, despite its positive impact on household food security, the adoption of combinations of improved agricultural technologies is usually hindered and/or facilitated by different factors. Relevant actors in R&D should have typically promoted the adoption of a combination of multiple technologies and designing possible interventions for those factors that impede the use of those technologies. The results of our study point out the following important implications. Although we have evidence of the superiority of adoption of multiple combinations of agricultural technologies on food security, our findings suggest that substantial efforts should be made by all actors to plan and implement campaigns to promote such technologies. In particular, it seems that awareness of farmers is needed and continuous efforts of all actors, particularly DA field assistance, are needed. Technology promotion alone is not a solution for the wider application of technologies, since there is always a significant gap between technology supply and demand; hence, it needs various management skills and intervention strategies. However, this study used a cross-sectional data set to analyze the determinants of the household decision to adopt multiple technologies, without sufficiently controlling the unobserved heterogeneity. Future research can provide more adequate and accurate information on the determinants by using panel data.

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