Estimating the Impact of Agricultural Technology Adoption on Teff Productivity: Evidence from North Shewa Zone of Amhara Region, Ethiopia[1]

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Abstract

This study aims to examine the impact of agricultural technology adoption on Teff productivity in the North Shewa Zone of the Amhara region, Ethiopia. The analysis is based on household-level data covering 395 households collected in 2021. Multinomial logit and multinomial endogenous switching regression models were used for analysis. The results of the study showed that agricultural technology adoptions are affected by the education level of the household head, off-farm employment, livestock ownership measured in tropical livestock units, access to credit, household's saving, access to extension service, farm size, and distance from the market. The results have also pointed out that the adoption of fertilizer and/or improved seed have increased teff productivity significantly. Furthermore, the adoption of a combined fertilizer and improved seed has provided higher productivity than adoption in isolation. Therefore, supporting agricultural technology adoption by increasing access to fertilizer and/or improved seed have significantly increased agricultural productivity.

Keywords: technology adoption, multinomial logit, multinomial endogenous switching regression, teff productivity, Ethiopia

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1. Introduction

In Ethiopia, agriculture is the main motor for the economy which accounts for about 80% of living. Its average share to the GDP is about 34.1%, employs about 79% of the population, accounts for 79% of foreign earnings. It is the major backbone of the raw material and capital for the investment and market (National Planning and Development Commission, 2018; Diriba, 2020). However, the sector still is characterized by lower productivity, subsistent production, and traditional farming systems. Thus, an increase in agricultural productivity is the primary requirement for overcoming problems of poverty, food insecurity, low income of the farm households, and low economic development of the country. Accordingly, the adoption of improved agricultural technology is one of the way for which agricultural productivity increased (Jayne et al., 2017; Admassie and Ayele, 2010). In Ethiopia, agricultural technology adoptions are strongly recommended to improve agricultural crop productivity. This is because in the countries with land paucity and rising problems of land degradation and population growth, agricultural production cannot be persistent without the application of agricultural technologies (De Janvry et al., 2000, 2017; Mohammed, 2014; Habtewold, 2018; Jayne et al., 2017).

Considering the importance of agricultural technologies in raising agricultural productivity, maintaining food security and reducing poverty, the government of the country has been promoting and implementing different agricultural technologies. For example, the adoption of tractor, machinery, improved seed, harvester, irrigation, pesticides, threshing grain, fertilizers, and sorting and packaging the products as well as new farming practices (Admassie and Ayele, 2010) are some to name a few. Although lots of efforts and investments have been made by the government of Ethiopian to promote, and disseminate the adoption of agricultural technologies, the agricultural technology adoption rate remains very low, resulting in lower agricultural productivity (Jayne et al., 2017; Abay et al., 2017; Natnael, 2019; Asmare et al., 2019). Therefore, the actual lower productivity of the sector is caused by the lower adoption rates of agricultural technologies. To this end, to gain more insight on the factors that determine the adoption and how adoption possibly increases productivity, this study looks at the determinants of the adoptions of fertilizer and/or improved seed and the implied impact on teff productivity in North Shewa zone. The author uses the adoption of fertilizer and/or improved seed adoption because the adoption of these technologies is widely used and have higher adoption rate in the study area compared to other technology packages.

Teff is one of the most extensively cultivated cereal crops in Ethiopia. It is the most dominantly consumed crop in the country (CSA, 2019). Recently, the crop is receiving worldwide attention for its nutritional and health-related benefits (Lee, 2018). It is providing the livelihoods for the majority of smallholder farmers and a strategic crop with the potential to enhance commercialization of smallholder agriculture and improve food security. In the country, the crop accounts more than 3 million hectare of grain crop area and as to production it accounts more than 54 million tones (CSA, 2019). Amhara region is the second largest Teff producer next to Oromia region in the country. The average productivity of Teff in the region is 2.29 tones per hectare which is very low (Minten et al., 2013). According to the report of National Teff Research Commodity Strategy 2016-2030, the productivity of Teff can be increased by 4.34 tones per hectare if farmers could adopt agricultural technologies (Abewa et al., 2020). Therefore, considering what factors affect smallholder farmers not to fully adopt the agricultural technologies and the motivations for such adoption is critical to accelerate the adoption process.

Besides, the use of agricultural technologies increases agricultural productivity and thus reduces poverty (De Janvry et al., 2000). There are few researches conducted so far on the impacts of agricultural technology adoption on Teff productivity in Ethiopia. For example; Abewa et al. (2020), Negussie (2020), Wolde (2021), Tamirat (2020), Natnael (2019), Vandercasteelen et al. (2016) and Berhe (2014) found that the adoption of agricultural technologies significantly raises Teff productivity.

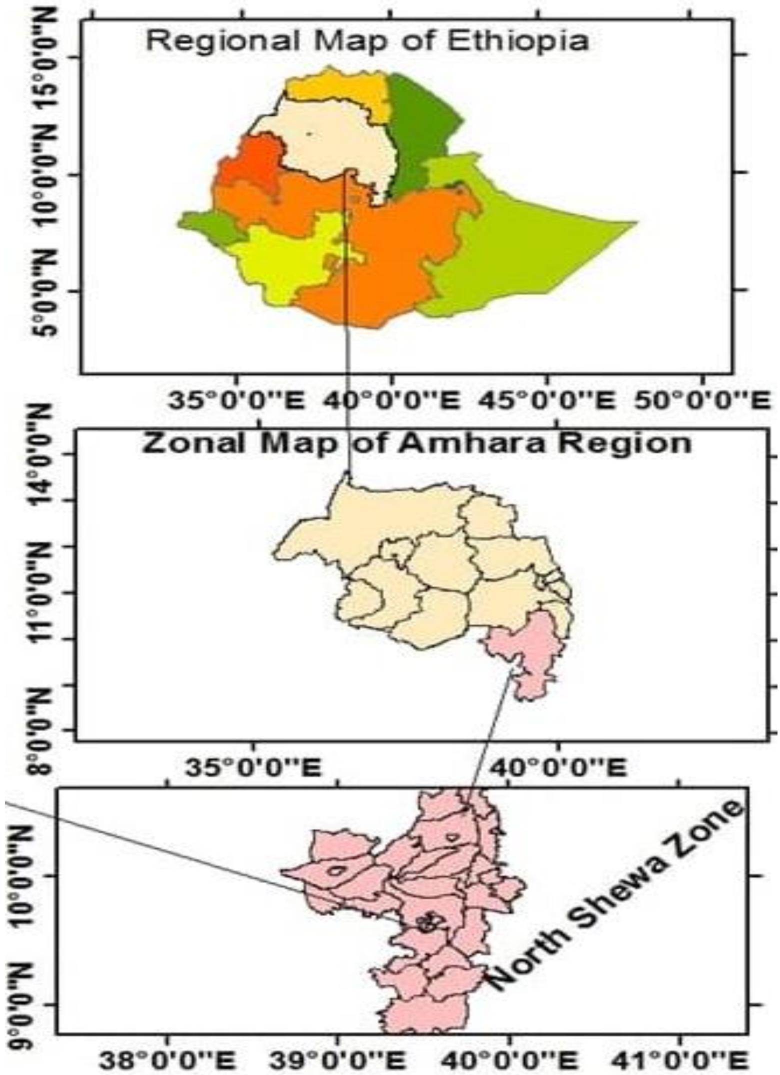
The contribution of the study to the current literature is three-fold. First, many studies have been conducted previously on the area examining the impacts of single agricultural technology adoption on Teff productivity (example, Vandercasteelen et al., 2016; Negussie, 2020; Wolde, 2021; Tamirat, 2020). However, this study examines the impact of multiple technology adoption on the productivity Teff because farmers adopt more than one technology in their crop fields. Second, most previous studies examined the impact of agricultural technology adoption on Teff productivity by employing ordinary least square (OLS) and Propensity Score Matching (PSM) models (for example, Abewa et al., 2020; Wolde, 2021; Tamirat, 2020; Natnael, 2019). However, these models do not show the true effect of agricultural technology adoption on Teff productivity because these models fail to form sufficient counterfactuals to capture the treatment effect, and assume no selection bias due to unobserved factors. But, in non-experimental studies of this kind, examining the impact of adoption on productivity is challenging mainly because of the existence of selection bias due to observed and unobserved factors (Belay and Mengiste, 2021). Therefore, this study used multinomial endogenous switching regression (MESR) model which solves the problem of selection bias, possible endogeneity, and counterfactual situations. Thirdly, researches on the impact of agricultural technology adoption on Teff productivity is less clearly documented in the study area. Therefore, this study aims to examine the impact of agricultural technology adoption on Teff productivity in North Shewa zone, Amhara region, Ethiopia.

2. Methodology

2.1 Study Area Profile

The study was conducted in North Shewa zone of the Amhara region of Ethiopia. The zone is one of the 10 zones in the region. It is bordered by the Oromia Region on the south and west, by South Wollo on the north, by the Oromia Zone on the northeast, and on the east by the Afar Region. On average, the yearly rainfall fluctuates between 400 – 700 mm and the yearly average temperature varies between -8 - 35.7oC. About 88.34% are rural inhabitants, of which 0.01% is pastoralists. Agriculture is the main livelihoods of the peoples of the zone. Among the major crops grown in the zone, teff, wheat, barley, maize, sorghum, millet, and pulse different types of Beas, pea, and lentil crops are the dominant product of the farmers (North Shewa Zone administrative office, 2020).

Figure 1: Geographical Location of North Shewa Zone



2.2 Data and Sampling Description

The study focused on teff farming households randomly selected from the two major teff growing districts of the zone. The study was conducted based on a household-level cross-sectional data collected from north Shewa zone farmers. The data for analysis were collected through a questionnaire that would allow the collection of demographic, socio-economic, and institutional characteristics. To select sample households, the study used the multi-stage sampling method. Firstly, from the total districts of the zone two districts specifically Minjar Shenkora and Moretna Jiru were selected purposively due its high potential to agricultural practices, the dominant teff producing districts of the zone and its topographical similarity. Following this, according to north Shewa zone administration office (2019), there are a total of 50640 households in the selected districts (Minjar Shenkora = 29359 households and Moretna Jiru =21281 households). For the second stage where simple random sampling method was used, the sample size (n) was determined as described in Yamane (1967) using the following formula:

$$\mathrm{n} = \frac{N}{1+N(e)^2} = \frac{50640}{1+50640(0.05)^2} = 397$$

Where n is the sample size, N is the total household size and e is level of precision. Hence the total sample size n = 397 was allocated to Minjar Shenkora ($n_1 = \frac{397}{50640} * 29359 = 230$) and to Moretna Jiru ($n_2 = \frac{397}{50640} * 21281 = 167$). As a result, 397 households were drawn as sample size in this study. Thirdly, from the total Kebeles of the selected districts, 15 Kebeles were randomly selected and lastly simple random sampling was used to select each sample respondent from each selected Kebeles. Due to missing information, 2 observations were dropped. Thus, 395 households were considered for the analysis.

2.3 Analytical Framework

The study employed descriptive and econometric approaches for data analysis. Descriptive analysis like mean and standard deviation were used to gain a better understanding of the demographic characteristics, socio-economic and institutional characteristics of the farm households. An econometric method such as an endogenous switching regression model was used to examine the impact of agricultural technology adoption on teff productivity in the study area.

2.4 Estimation Strategy and Model Specification

In the adoption theory, farm households' adoption of the technology is expected to be based on their expected profit/gain from adoption of a specific choice given his/her constraints. This implies adoption occurs if the utility of the chosen package is higher than the utility of the other alternatives. However, the utility that is gained from adopting agricultural technology is not observed but only it's a choice of technology, one can assume a random utility model which states conditional probability choice given farmers' choice (Verbeek, 2005).

Measuring the impact of fertilizer and/or improved seed adoption on teff productivity requires controlling for endogeneity problem, possible selection bias and unobserved heterogeneity issues. In response to this, the MESR model is potential to solve these problems. Following Kassie et al. (2015, 2018), Tesfay (2020), Mohammed (2014), Danso-Abbeam & Baiyegunhi, (2018) and Teklewold et al. (2013) farm households' decision to adopt alternative agricultural technologies and its impact on outcome variable (yield in this case) was modeled using Multinomial Endogenous Switching Regression model (MESR). The model is estimated in two stages. In the first stage, the farm households' decision to adopt alternative technology packages was estimated using multinomial logit selection model (MNL). In the second stage, the impact of each alternative technology packages on teff productivity were estimated using ordinary least squares (OLS) with a selectivity correction term from the first stage due to time-varying unobserved heterogeneity.

Assume that farm households aim to maximize their utility (U_i) – such that productivity in this case, by comparing with alternate package h. For the i^{th}farm household faced with J alternative technology sets, choice of alternative technology j over any alternative package h implies that $U_{ij} > U_{ih}\ for\ all\ other\ h \neq j$. The expected utility of the farm households from adopting technology package j (U_{ij}^*) is a latent variable determined by observed household, plot, and institutional characteristics (X_i) and unobserved characteristics (ε_{ij}):

$$\boldsymbol{U_{ij}^* = X_i \beta_j + \varepsilon_{ij}} \qquad (\mathbf{1})$$

Where X refers to a set of observed explanatory variables determine technology adoption and ε_{ij} is error term. Let T_{ij} be an index that indicates the choice the farmer has made - it equals 1 if the household has adopted the fertilizer, equals 2 if the household has adopted the improved seed and equals 3 if the household has adopted a combination of fertilizer and improved seed technology and 0 if non-adoption, such that:

$$T_{ij} = \begin{cases} 0 \text{ iff } & U_{i0}^{*} > \max_{h \neq j}(U_{ih}^{*}) \quad \text{or} \quad \mu_{i0} < 0 \\ . & . \qquad\qquad\qquad . \\ . & . \qquad\qquad\qquad . \\ . & . \qquad\qquad\qquad . \\ J \text{ iff } & U_{iJ}^{*} > \max_{h \neq j}(U_{ih}^{*}) \quad or \quad \mu_{iJ} < 0 \end{cases}$$

Where μ_{ij} is the expected difference in utility (productivity) between alternative technology packages j and h. Hence, i^{th} farm households will adopt alternative technology package j if (and only if) $\mu_{ij} = \max_{h \neq j}(U_{ij}^{*} - U_{ih}^{*}) > 0$.

It is assumed that the error terms ε_{ij} are independent and identically distributed that is under the assumption independence of irrelevant alternatives (IIA) hypothesis in the MNL. The MNL model can be specified as:

$$P_{ij} = Pr(\varepsilon_{ij} < 0 | X_i = j) = \frac{\exp(X_i \alpha_i)}{\sum_{j=1}^{3} \exp(X_i \alpha_i)} \qquad (\mathbf{2})$$

Where i indicate an individual farm household; j represents the technology choice set; Xi represents is a set of observed household demography, socioeconomic, plot, institutional and locational factors that affects the decision of adopting; and β_j are unknown parameters to be estimated. The parameters of the latent variable are estimated with maximum likelihood estimation.

Secondly, the outcome equation, the impact of agricultural technology adoption on teff productivity (productivity measured as quintal per hectare) is estimated using MESM. The model runs a separate regime for the adopters of alternative technologies and non-adopters so as to accounting for endogeneity and selection biases. Suppose agricultural productivity is specified Pij for adopters of alternative technologies and Pi0 for non-adopters. Thus, the outcome equations for each regime are stated as follows:

$Regime\ 0\ (not\ to\ adopt)$:

$$P_{i0} = \alpha_0 X_{i0} + e_{i0} \quad if\ T_i = 0 \tag{3}$$

$Regime\ j\ (to\ adopt)$:

$$P_{ij} = \alpha_{ij} X_{ij} + e_{ij} \quad if\ T_i = 1, 2, 3 \ldots \mathrm{m} \tag{4}$$

Where Pij, the outcome variables, represents teff productivity for non-adopter and adopters - observed if and only if package j is adopted, where $U_{ij} > U_{ih}\ for\ all\ other\ j \neq h.$, X_i denote a set of explanatory variables that influence teff productivity; α_i are parameter to be estimated, and e_i represents error terms. If the error terms in equations (1) (3) and (4) are not independent and identically distributed, a consistent OLS estimate of parameters needs the addition of the selection correction terms of the alternative choices in equations (2) and (3). Given this, consistent estimates can be found by adding the selectivity correction terms (mills ratio) generated from the adoption equation (Teklewold et al., 2013). Then the consistent estimates of the MESR can be specified as:

$Regime\ 0\ (not\ to\ adopt)$:

$$P_{i0} = \alpha_0 X_{i0} + \gamma\hat{\lambda}_{i0} + \varphi_{i0} \quad if\ T_i = 0 \tag{5}$$

$Regime\ j\ (to\ adopt)$:

$$P_{ij} = \alpha_{ij} X_{ij} + \gamma\hat{\lambda}_{ij} + \varphi_{ij} \quad if\ T_i = 1, 2, 3..\mathrm{m} \tag{6}$$

Where γ_i is the covariance between ε's and φ's, λ_j is the inverse Mills ratio computed from the estimated probabilities in Eq. (2) as follows:

$$\hat{\lambda} = \sum_{j}^{m} \rho_j \left(\frac{\hat{P}_{im} \ln(\hat{P}_{im})}{1 - \hat{P}_{im}} + \ln(\hat{P}_{ij}) \right)$$

Where ρ is the correlation coefficient of ε and φ. In the multinomial choice setting, there are $J - 1$ selection correction terms. Practically, the models in equations (5) and (6) has heteroscedasticity problem that arise from the computation of inverse mills ratio λ_j. Hence, standard errors are bootstrapped to account the problem.

According to Di Falco et al. (2010) and Belay and Mengiste (2021), for the MESR model to be adequately identified, it is important to use exclusion restriction due to the endogenous nature of technology adoption decisions. Exclusion restriction test refers to in excluding explanatory variables that affect the selection equation directly but not the outcome equation. The reason for this is that the inverse Mill's ratio is a non-linear function of the explanatory variables in the adoption equation. Thus, the second stage equation is identified because of this non-linearity. But, the non-linearity of the inverse Mill's ratio is not normally tested or justified. Hence, so as to make the source of identification clear, it is worthwhile to have an explanatory variable in the adoption equation, which is not included in the outcome equation. Therefore, this study used variables of extension visit, farmers' cooperative, distance from the road and from the market as instruments to correct for selection. The result demonstrates that the selected instruments are insignificant on the outcome equations at a 1% level. This approves the validity of the selected instruments and the model is adequately identified, as reported in Appendix 1.

2.4.1 Treatment Effects of Adoption

The MESR model allows us to estimate the average treatment effects of adoption under actual and counterfactual scenarios; and can be specified as follows:

Adopters with adoption (actual):

$$E\left[P_{ij} \mid T = 1,2,3\right] = \alpha_{ij}X_{ij} + \gamma_{ij}\varepsilon\hat{\lambda}_{ij} \tag{7}$$

Non-adopters without adoption (actual)

$$E[P_{i0} \mid T = 0] = \alpha_{i0}X_{i0} + \gamma_{i0}\varepsilon\hat{\lambda}_{i0} \tag{8}$$

Adopters had they decided not to adopt (counterfactual)

$$E\left[P_{ij} \mid T = 0\right] = \alpha_{i0}X_{ij} + \gamma_{i0}\varepsilon\hat{\lambda}_{ij} \tag{9}$$

Non-adopters had they decided to adopt (counterfactual)

$$E[P_{i0} \mid T = 1,2,3] = \alpha_{ij}X_{i0} + \gamma_{ij}\varepsilon\hat{\lambda}_{i0} \tag{10}$$

The difference between eq. (7) and eq. (9) yields the average treatment effect of teff productivity on the treated (TT); and specified as:

$$ATT = E\left[P_{ij} \mid T = 1,2,3\right] - E\left[P_{ij} \mid T = 0\right] = X_{ij}\left(\alpha_{ij} - \alpha_{io}\right) + \hat{\lambda}_{ij}\left(\gamma_{ij}\varepsilon - \gamma_{i0}\varepsilon\right) \quad \textbf{(11)}$$

On the other way, the difference between eq. (10) and eq. (8) gives the average treatment effect of teff productivity on the untreated (TU); and defined as:

$$ATU = E[P_{i0} \mid T = 1,2,3] - E[P_{io} \mid T = 0] = X_{i0}\left(\alpha_{ij} - \alpha_{i0}\right) + \hat{\lambda}_{i0}\left(\gamma_{ij}\varepsilon - \gamma_{i0}\varepsilon\right) \quad \textbf{(12)}$$

The difference between eq. (11) and eq. (12) provides in transitional heterogeneity (TH) that shows whether the effect of adoption is higher or lower for the adopters than the non-adopters.

Table 1: Description and measurement of variables and hypothesis of the study

Explanatory Variables[19]	Description and measurement	Expected Sign
Sex	Sex of the household head = 1 if male; 0 if female	+/-
Education	Education level of the household head = 0 if illiterate; 1 if grade 1-8; 2 if grade 9-12; 3 if above grade 12	+
Access to credit	=1 if the farm household had taken loan; 0 otherwise	+
Off-farm Employment	=1 if the farm household had participated; 0 otherwise	+/-
Saving	=1 if the farm household had saving in formal financial institution; 0 otherwise	+
Extension visit	=1 if a household had an extension visit during their practice; 0 otherwise	+
Farm cooperative	=1 if the household is a member of farm cooperative; 0 otherwise	+
Age	Age of the household head, measured in years	+/-
Family size	The total number of household size	+/-
TLU	Total Livestock herd size of the household measured in Tropical Livestock Unit (TLU)	+/-
Farm size	Total farm size of the household in hectare	+
Distance from market	Distance from home to the nearest market (in kilometers)	-
Distance from all-weather road	Walking distance from home to all road centers (in kilometers)	-

[19] Selection of the variables used in this study are based on previous studies (e.g. Admassie and Ayele 2010; Sebsibe et al. 2015; Mohammed 2014; Kassie et al. 2018; Ayenew et al. 2020; Belay and Mengiste 2021).

3. Results and Discussion

This section provides results of the determinants of agricultural technology adoption (adoptions of fertilizer and/or improved seed) and their implied impact on the productivity of Teff crop of the zone.

3.1 Descriptive Statistics

Table 2 summarizes the possible alternative technology adoptions used in the study. Out of the total 395 sampled farm households, about 21.27% are non-adopters (F0I0), whereas 26.08% and 15.95% of them adopted fertilizer (F1I0) and improved seed (F0I1), respectively, and finally, about 36.71% of them have adopted a combination of fertilizer and improved seed (F1I1).

Table 2: Alternative technology adoption and their frequency

Choice	Binary package	Fertilizer		Improved seed		Frequency	Percentage
		Fo	F1	Io	I1		
1	F0I0	√		√		84	21.27
2	F1I0		√	√		103	26.08
3	F0I1	√			√	63	15.95
4	F1I1		√		√	145	36.71

Note: Each element in the combination is a binary variable and for fertilizer (F) and improved seed adoption (I), and the subscripts represent 1 = adoption and 0 = non-adoption.
Source: Author's estimate, 2021

Table 3 provides the summary of explanatory variables for the adopters and non-adopters. The result shows that most of the household heads in the adopters' group are male-headed households, household heads in the adopters' group are older, and have higher educational level as compared to the non-adopters. On average, adopters have higher farm size and livestock assets than the household heads in the non-adopters' group. Moreover, the farm households from the adopters' group are more likely to engage in off-farm activities, have higher rates of saving, higher rates of access to credit, extension visits and farm cooperatives than the households from the non-adopters' group. Additionally, on average, farm households in the adopters' group are located near to the market and urban centers than the non-adopters. Therefore, the result confirms that the household, socio-economic and institutional characteristics are relatively high for adopters as compared with the non-adopter ones.

Table 3: Summary of Variables used for the Regressions

Explanatory Variables	Category	Adopters			Non-Adopters
		F1I0	F0I1	F1I1	F0I0
Sex	Male	95(92.23)	56(88.89)	135(93.10)	79(94.05)
	Female	8(7.77)	7(11.11)	10(6.90)	5(5.95)
Education	Illiterate	46(44.66)	24 (38.10)	43(29.66)	44(52.38)
	1-8	46(44.66)	30 (47.62)	73(50.34)	30 (35.71)
	9-12	11(10.68)	8(12.70)	21(14.48)	8 (9.52)
	>12	0	1(1.59)	8(5.52)	2(2.38)
Access to credit	Yes	61(59.22)	29 (46.03)	71(48.97)	37 (44.05)
	No	42(40.78)	34 (53.97)	74(51.03)	47 (55.95)
Off-farm Employment	Yes	67(65.05)	44 (69.84)	91(62.76)	44 (52.38)
	No	36(34.95)	19 (30.16)	54(37.24)	40 (47.62)
Saving	Yes	93(90.29)	58 (92.06)	122(84.14)	69 (82.14)
	No	10(9.71)	5 (7.94)	23(15.86)	15 (17.86)
Extension visits	Yes	94(91.26)	61 (96.83)	314(95.15)	70 (83.33)
	No	9(8.74)	2 (3.17)	16(4.85)	14 (16.67)
Farm cooperative	Yes	192(84.21)	40 (75.47)	141(97.24)	142 (76.76)
	No	36(15.79)	13 (24.53)	4(2.76)	43 (23.24)
	(Percents' in parenthesis)				
Age	Mean	42.203	41.539	43.841	44.142
	SD	(11.12)	(11.85)	(11.18)	(13.00)
Family size	Mean	4.941	5.0	4.875	5.0
	SD	(2.09)	(1.75)	(2.18)	(2.24)
TLU	Mean	6.466	6.21	6.022	5.353
	SD	(4.55)	(3.94)	(3.88)	(3.58)
Farm size	Mean	1.463	1.465	1.876	1.294
	SD	(.551)	(.403)	(.822)	(.522)
Distance from market	Mean	5.232	5.283	4.807	5.998
	SD	(5.16)	(5.78)	(5.74)	(5.51)
Distance from all-weather road	Mean	3.489	3.592	3.246	3.703
	SD	(3.78)	(4.20)	(4.98)	(5.83)

3.2 Empirical Analysis

3.2.1 Determinants of Agricultural Technology Adoption

Table 4 presents the estimated results of the multinomial Logit model. The reference or base category of the model is non-adopter (F0I0). Before the estimation, the author performed different tests. The result of the Wald test has shown that we reject the null hypothesis that all regression coefficients are jointly equal to zero (Chi2(45) = 1118.23: P > chi2 = 0.000). The Hausman test result for test of IIA assumption shows that all the alternative packages are unique with respect to the variables in the model, as presented in Appendix 2. The results of the test of multicollinearity problem have indicated that there is no serious multicollinearity problem across the explanatory variables, see Appendix 3. And finally, robust regression is used to control for the heteroscedasticity problem.

The result have shown that the coefficient of the education level of the household head is positive and significant for the adopters of fertilizer (F1I0) and a mix of fertilizer and improved seed (F1I1) as it is expected, implying that educated farmers are more likely to adopt a combination of fertilizer and improved seed technology (F1I1) simultaneously more than the non-educators one. This is because education enables people to acquire, analyze and evaluate information on modern technology, market opportunity and its implied benefits. This finding is in line with the works of Belay and Mengiste (2021).

The coefficient of off-farm participation is positive and significantly influences the adoption of F0I1 and F1I1 packages as it is expected, implying that those farmers joining in off-farm activities are more likely to adopt (F1I1) than the non-adopter. This is because farm households can generate additional income, and used to solve the problem that the farm household's faces while intending to purchase farm technologies. The finding is similar with the finding of Sebsibe et al. (2015). The coefficient of saving is positive and significant on the adopters of F1I1 as it expected, indicating that households who had saved money are more expected to adopt F1I1 adopters. This is because saving serves as a means of overcoming liquidity constraints and a means of buying inputs for agricultural production. This is consistent with Belay and Mengiste (2021), and Natneal (2019).

The coefficient of TLU is significant and indicates that TLU is positively associated with the adoption of fertilizer (F1I0) and improved seed (F0I1), as it is expected. This is because farm household's having livestock asset is more likely to adopt F1I0 and F0I1 than those who do not have. This is because of farmers who possess a flock of livestock are more likely to adopt than the have-not as it helps to get improved technologies as it serves as a source of income and inputs for fertilizer. This finding is in line with the findings of Admassie & Ayele (2010). Farm size is another important factor that has a positive and significant influence on adopting all technology packages used in the study, implying that households owing large farm sizes are more expected to adopt than households who have less. This is true because as operated farm size increases, the likelihood of farmers considering farming activity as full time or way of life increases: and hence more likely motivated towards adopting agricultural technologies. This implies that greater land size serves as a security against the risk of crop failure. The result is parallel to the works of Feyisa (2020).

The coefficient of credit access is positive and significant for the adoption of F1I0 and F0I1 as it is expected, implying that households who get credit service are more likely to adopt F1I0 and F0I1 technologies than their counterparts. This is because getting credit significantly reduces liquidity constraints that households could face while they want to purchase agricultural technologies (Mohammed, 2014; Belay and Mengiste, 2021). The coefficient of extension visit is positive and significant for the adoptions of all combinations used in the study. As it is expected, having an extension visit during the adoption practice of agricultural technologies are more likely to adopt F1I0, F0I1 and F1I1 than those who do not have. This is because an extension visit provides the required information to the farm households regarding the characterization, sources, application, and importance of the technology. This is in line with Ayenew et al. (2020), Admassie and Ayele (2010).

Lastly, the coefficient of distance from the market is negative and significant for the adoption of all technology packages used in this study as it is expected, implying that households living nearer the market places are more likely to adopt F1I0, F0I1 and F1I1 technologies than their counterparts. This is because farmers may have higher access to information on improved agricultural technologies, and also could lead to timely adoption, and lower production cost, and hence are likely to adopt. The finding of the study is consistent with (Sebsibe et al., 2015; and Mohammed, 2014).

Table 4: Maximum Likelihood Estimates for the multinomial Logit model

Base category: Non-adopters	**Adopters of**		
	F1I0	**F0I1**	**F1I1**
Variables	**Coefficient (SE)**	**Coefficient (SE)**	**Coefficient (SE)**
Sex	-0.570 (0.678)	-0.846 (0.641)	-0.404 (0.681)
Age	-0.014 (0.016)	0.020 (0.017)	0.009 (0.014)
Family size	0.026 (0.068)	0.003 (0.093)	0.039 (0.089)
Education (base: illiterate)			
Grade 1-8	0.180 (0.350)	0.524 (0.388)	0.822(0.340)**
Grade 9-12	-0.033 (0.551)	0.529 (0.587)	0.873 (0.531)
Grade >12	1.386 (0.079)***	0.660 (1.192)	2.663 (0.930)***
Off-farm employment	-0.017 (0.038)	0.738 (0.369)**	0.352 (0.028)***
TLU	0.111 (0.042)**	0.030 (0.014)**	0.328 (0.039)
Saving	0.110 (0.516)	0.648 (0.565)	0.616 (0.304)**
Distance to market	-0.114 (0.024)***	-0.110 (0.043)**	-0.106(0.018)***
Distance to all-weather road	-0.017 (0.038)	-0.011 (0.041)	-0.005 (0.042)
Extension visit	0.661 (0.051)***	1.834 (0.892)**	2.767 (0.910)***
Credit access	0.661 (0.330)**	0.046 (0.013)***	0.166 (0.317)
Farm cooperative	0.784 (0.626)	-0.468 (0.607)	0.437 (0.640)
Farm size	0.665 (0.348)*	0.634 (0.350)*	1.648 (0.349)***
Constant	-1.353 (1.208)	-3.662 (1.372)***	-5.196 (1.390)***

Obs. 395; Wald Chi2 (45) = 1118.23; *P* > chi2 = 0.000; Log pseudolikelihood = -467.40809; Robust regression

Note: ***significant at 1% level; **significant at 5% level; *significant at 10% level; Standard errors in parenthesis.

Source: Author's estimate, 2021

3.2.2 Impact of Agricultural Technology Adoption on Productivity

This section discusses the impact of agricultural technology adoption on teff productivity in the study area. In response to the impact evaluation pitfalls, a multinomial endogenous switching regression model is employed. The model results show that the self-selection problem is apparent in the data. Specifically, the mills' ratio values are significant, implying that using the model is appropriate. The falsification test results show that (Prob > F = 0.2808) the selected instruments are valid and the model is adequately identified, as they are highly insignificant at 1% level, see Appendix 1.

Table 5 presents the conditional average treatment effects of adoption of a combination of alternative packages on teff productivity. The study compares the value of teff productivity under the actual case that have adopted with the counterfactual case which had not adopted. The true average treatment effect of adoption of fertilizer and/or improved seed on teff productivity is estimated by comparing the actual productivity with the respective counter-factual scenario. The results show that adopters have significantly larger productivity per quintal than the non-adopters. That is to say, actual adopters have increased their productivity and actual non-adopters if they decided to adopt, their productivity would increase as well. Specifically, the adoption of mix of fertilizer and improved seed (F1I1) results in high productivity (21.31 quintals per hectare) followed by the adoptions of fertilizer package only (F1I0) productivity (17.10 quintals/ha) and by the adoptions of improved teff seed only (F0I1) productivity (15.95 quintals/ha). The average treatment effect has shown farm households increased their productivity by 9.227, 7.042 and 5.709 quintals/ha from adopting full technology (F1I1), fertilizer only (F1I0) and improved seed only (F0I1) respectively.

Conversely, the average treatment effect on the non-adopters is 9.48 quintal per hectare, which will increase by 11.994, 7.063 and 5.692 quintals per hectare if they decide to adopt full technology (F1I1), fertilizer only (F1I0) and improved seed only (F0I1) respectively. Therefore, the result confirms that the adoptions of fertilizer and/or improved seed significantly increase teff productivity in the study area. The negative significant values of transitional heterogeneity effect (TH) for the adoption of fertilizer and improved seed (F1I1), would mean that the effect of adoption would be significantly lower for the farm households who adopted than those who did not adopt.

Thus, the results of the study demonstrate that the adopters of fertilizer and/or improved seed significantly increases teff productivity than non-adopters. Moreover, full technology adopters are more productive than single technology adopters. The finding of the study is similar to previous works of Abewa et al. (2020), Wolde (2021), Tamirat (2020), Natnael (2019) and Tiruneh and Bizuayehu (2021).

Table 5: Estimation of Conditional Expectations and Treatment Effect using MESM

Alternative		Decision stage		
		To Adopt	**Not to adopt**	**Adoption Effect**
Adopters of	F1I0	17.10 (.297)	10.06" (.243)	TT1 = 7.042***
	F0I1	15.95 (.278)	10.24" (.300)	TT2 = 5.709***
	F1I1	21.31 (.075)	12.08" (.300)	TT3 = 9.227***
Non-adopters	F0I0	16.54" (.332)	9.48 (.289)	TU1= 7.063***
	F0I0	15.17" (.274)		TU2= 5.692***
	F0I0	21.47" (.085)		TU3= 11.994***
				TH1 = -.0205
				TH2 = .0169
				TH3 = -2.766***

Notes: TT = Adoption effect for adopters, TU = Adoption effect for non-adopters, TH (TT-TU) = transitional heterogeneity

Standard errors in parenthesis, and ***, ** denotes significance level at 1% and 5% respectively.

Source: Authors’ estimates, 2021

4. Conclusion

The study has examined the impact of the adoption of fertilizer and/or improved seed on teff productivity in the North Shewa zone of the Amhara region of Ethiopia. The study has used multinomial endogenous regression model to estimate the determinants of agricultural technology adoption and the implied impact on the productivity. The results of the selected equation show that the adoption of fertilizer and/or improved teff variety decision by households is positively and significantly influenced by the education level of the household head, off-farm participation, livestock ownership measured in tropical livestock units, credit access, and saving and extension visit. Furthermore, the adoption of fertilizer and/or improved teff variety decision by households is negatively and significantly affected by distance from the market. The results of the outcome equation have indicated that the adoption of fertilizer and/or improved seed technologies has a direct impact on increasing teff productivity in the study area. Thus, finding has also confirmed the potentially positive role of agricultural technology adoption in raising crop productivity. Besides the study suggests that the concerned bodies or policymakers need to support and promote the adoption of fertilizer and/or improved seed technologies to exploit the productivity effects of agricultural technology adoption.

More specifically, it is recommended that policies that aim to encourage and expand the adoption of new or improved alternative agricultural technology and a combination of agricultural technologies will have a substantial impact on improving crop productivity. The government at Zone, region and federal level should strengthen the local policy level interventions and increase access to credit and agricultural extension services. With regard to distance from market, the concerned body should have to provide/create the necessary input/output markets near to the farm households. Moreover, education will help the farm households learn about the potential merits and demerits of adopting agricultural technologies without any intermediary. Therefore, government should invest heavily to increase the literacy rate among the rural farmers.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

References

Abay, K. A., Blalock, G., & Berhane, G. (2017). Locus of control and technology adoption in developing country agriculture: Evidence from Ethiopia. *Journal of Economic Behavior & Organization*, 143, 98–115.

Abewa, D., Merie, H. E., & Kassa, M. (2020). Prevalence and Associated Factors of Agricultural Technology Adoption and Teff Productivity in Basso Liben District, East Gojjame Zone, North west Ethiopia. bioRxiv.

Admassie, A., & Ayele, G. (2010). Adoption of improved technology in Ethiopia. *Ethiopian Journal of Economics*, 19(1), 155-179.

Asmare, F., Teklewold, H., & Mekonnen, A. (2019). The effect of climate change adaptation strategy on farm household's welfare in the Nile basin of Ethiopia: Is there synergy or trade-offs? *International Journal of Climate Change Strategies and Management.*

Ayenew, W., Lakew, T., & Kristos, E. H. (2020). Agricultural technology adoption and its impact on smallholder farmers welfare in Ethiopia. *African Journal of Agricultural Research*, 15(3), 431–445.

Belay, M., & Mengiste, M. (2021). The ex-post impact of agricultural technology adoption on poverty: Evidence from north Shewa zone of Amhara region, Ethiopia. *International Journal of Finance & Economics.*

Berhe, Y. (2014). The impact of row planting of teff crop on rural household income: A case of Tahtay Maychew Wereda, Tigrai, Ethiopia. Mekelle University, College Business and Economics, Department of Economics.

CSA (Central Statistical Agency). (2019). Agricultural sample survey 2018/2019: volume I report on area and production of major crops (private peasant holdings, meher season). In Statistical Bulletin. Addis Ababa.

Danso-Abbeam, G., & Baiyegunhi, L. J. (2018). Welfare impact of pesticides management practices among smallholder cocoa farmers in Ghana. Technology in Society, 54, 10-19.

De Janvry, A., Macours, K., & Sadoulet, E. (2017). Learning for adopting: Technology adoption in developing country agriculture (p. 120). Ferdi

De Janvry, A., Graff, G., Sadoulet, E., & Zilberman, D. (2000). Technological change in agriculture and poverty reduction. Concept paper for WDR on poverty and development, 2001.

Di Falco, S., Veronesi, M., & Yesuf, M. (2011). Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. *American Journal of Agricultural Economics*, 93(3), 829-846.

Diriba, G. (2020). Agricultural and rural transformation in Ethiopia: Obstacles, triggers and reform considerations, Addis Ababa, Ethiopia: Ethiopian Economics Association

Feyisa, B. W. (2020). Determinants of agricultural technology adoption in Ethiopia: A meta-analysis. Cogent Food & Agriculture, 6(1), 1855817.

Jayne, T. S., Yeboah, K., & Henry, C. (2017). The future of work in African agriculture trends and drivers of change, Geneva, Switzerland: International Labour Office.

Habtewold, T. M. (2018). Adoption and impact of improved agricultural technologies on rural poverty. In Economic Growth and Development in Ethiopia (pp. 13-38). Springer, Singapore.

Kassie, M., Marenya, P., Tessema, Y., Jaleta, M., Zeng, D., Erenstein, O., & Rahut, D. (2018). Measuring farm and market level economic impacts of improved maize production technologies in Ethiopia: Evidence from panel data. *Journal of agricultural economics*, 69(1), 76-95.

Kassie, M., Teklewold, H., Marenya, P., Jaleta, M., & Erenstein, O. (2015). Production risks and food security under alternative technology choices in Malawi: Application of a multinomial endogenous switching regression. *Journal of Agricultural Economics*, 66(3), 640-659.Lee, H. (2018). Teff, a rising global crop: Current status of teff production and value chain. The Open Agriculture Journal, 12(1).

Minten, B., Tamru, S., Engida, E., & Kuma, T. (2013). Ethiopia's value chain on the move: the case of teff. ESSP Working Paper series 52, 1-26.

Mohammed, A. (2014). Adoption of multiple sustainable agricultural practices and its impact on household income: Evidence from maize-legumes cropping system of Southern Ethiopia. *International Journal of Agriculture*, 4, 196–203.

National Planning and Development Commission. (2018). Poverty and Economic Growth in Ethiopia (1995/96-2015/16). Federal Democratic Republic of Ethiopia. Addis Ababa, Ethiopia.

Natnael, A. B. (2019). Impact of technology adoption on agricultural productivity and income: A case study of improved teff variety adoption in north eastern Ethiopia. Agricultural Research & Technology: *Open Access Journal*, 20(4), 556139. https://doi.org/10.19080/ARTOAJ.2019.20.556139

Negussie, F. A. (2020). Impact of row planting teff technology adoption on the income of smallholder farmers: The case of Hidabu Abote District, North Shoa Zone of Oromia Region, Ethiopia. *International Journal of Agricultural Science and Food Technology*, 6(2), 195-203.

North Shewa Zone Administration Office. (2020). Number of populations of the zone, Debre Berhan: North Shewa Zone CSA office.

Sebsibe, S., Asmare, W., & Endalkachew, T. (2015). Agricultural technology adoption and rural poverty: a study on smallholders in Amhara regional state, Ethiopia. *Ethiopian Journal of Economics*, 23(683-2017-950), 117-156.

Tamirat, N. (2020). Impact Analysis of Row Planting Teff Crop Technology on Household Welfare: A Case Study of Smallholder Farmers of Duna District in

Hadiya Zone, Ethiopia. Journal of Economics and Sustainable Development, 11(5), 4-9.

Teklewold, H., Kassie, M., Shiferaw, B., & Köhlin, G. (2013). Cropping system diversification, conservation tillage and modern seed adoption in Ethiopia: Impacts on household income, agrochemical use and demand for labor. Ecological Economics, 93, 85-93.

Tesfay, M. G. (2020). Does fertilizer adoption enhance smallholders' commercialization? An endogenous switching regression model from northern Ethiopia. Agriculture & Food Security, 9(1), 1-18.

Tiruneh, E. S., & Wassie, S. B. (2020). Adoption and ex-post impact of alternative teff production technologies: micro-level evidence from Ethiopia. Agrekon, 59(3), 321-336.

Vandercasteelen, J., Dereje, M., Minten, B., & Taffesse, A. S. (2016). Row planting teff in Ethiopia: Impact on farm-level profitability and labor allocation. (Vol. 92). Intl Food Policy Res Inst.

Verbeek, M. (2008). *A guide to modern econometrics*. John Wiley & Sons.

Wolde, T. G. (2021). Impact of Row-Seeding Technology Adoption on Teff Productivity, Household Welfare and asset holding: Evidence from South West Shoa Zone, Oromia Regional State, Using Propensity Score Matching Technique. Innovations, 66(4), 1157-1171.

Yamane, T. (1967). *Statistics an Introductory Analysis* (2nd ed.). Harper and Row.

Appendix 1: Falsification Test (OLS Regression)

Linear regression

Productivity	Coef.	St.Err	t-value	p-value	[95% Conf.	Interval]	Sig
Distance from all-weather road	.19	.199	0.96	.342	-.205	.585	
Farm cooperative	-1.077	2.318	-0.46	.644	-5.69	3.537	
Distance from market	.13	.146	0.89	.376	-.16	.419	
Extension visit	-1.21	1.727	-0.70	.486	-4.648	2.228	
Constant	10.135	2.569	3.94	0	5.021	15.249	***

Mean dependent var	9.481	SD dependent var	5.767
R-squared	0.061	Number of obs	84
F-test	1.291	Prob > F	0.281
Akaike crit. (AIC)	536.433	Bayesian crit. (BIC)	548.587

*** p<.01, ** p<.05, * p<.1

Appendix 2: Hausman IIA specification Test

	Coef.
Chi-square test value	0.000
P-value	1.000

Appendix 3: Multicollinearity test

Variance inflation factor

	VIF	1/VIF
Distance from market	1.742	.574
Distance from all-weather road	1.692	.591
Family Size	1.313	.762
Age	1.303	.768
TLU	1.092	.915
Total land Size	1.006	.994
Mean VIF	1.358	.

Matrix of correlations for categorical variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) SeX	1.000						
(2) Education	-0.033	1.000					
(3) Saving	-0.001	0.071	1.000				
(4) off-farm partici~n	-0.006	0.179	0.138	1.000			
(5) credit	0.096	0.031	0.157	0.007	1.000		
(6) EXtenSion	0.029	-0.043	0.117	0.021	-0.048	1.000	
(7) farm cooperativ~r	0.066	-0.018	0.345	-0.019	0.049	0.032	1.000

Appendix 4: Multinomial Endogenous Switching Regression Result
Dependent variable: Teff Productivity (Quintal/hectare), inverse Mills ratio

Variable	F0I0	F1I0	F0I1	F1I1
	Coffe.(SE)	Coffe.(SE)	Coffe.(SE)	Coffe.(SE)
M0		-4.006***(1.168)	-.057 (.541)	-2.205**(1.050)
M1	-1.728(1.772)		-.544 (1.52)	-3.771***(1.277)
M2	.185(.481)	3.171**(1.369)		4.382**(1.695)
M3	1.607(1.657)	1.484 ***(.301)	.560 (1.013)	

*** p<.01, ** p<.05, * p<.1