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Adoption and ex-post impact of alternative *teff* production technologies: micro-level evidence from Ethiopia

Etsehiwot Semreab Tiruneh[a] and Solomon Bizuayehu Wassie[b]

[a]Debre Berhan University, Debre Berhan, Ethiopia; [b]Department of Agricultural Economics, Bahirdar University, Bahirdar, Ethiopia

ABSTRACT

Using plot-level data from Ethiopia, this study aims to examine the determinants and impact of alternative *teff* production technologies on the productivity and profitability of smallholder *teff* producers. The study employed a multinomial endogenous switching regression (MESR) model that accounts for selection bias due to observable and unobservable factors. The authors' results show that technology adoption has a positive association with education, farm size, extension visits, community meetings and asset ownership. On the contrary, distance to input and output markets have a negative and significant effect on the adoption of alternative *teff* production technologies. The MESR model results reveal that, while full technology adoption is the most productive and profitable option, adopting any of the alternative technologies also substantially improves the productivity and profitability of smallholder *teff* producers. The results also suggest that row-planting technology has a positive impact on the productivity and profitability of smallholder *teff* producers only when it is adopted with improved seed technology.

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Adoption; impact evaluation; agricultural technologies; *teff*; Ethiopia

1. Introduction

In the context of developing countries, agricultural productivity is the most important determinant of food availability – i.e., an element of food security (Di Falco, Veronesi, and Yesuf 2011). Hence, the issue of agricultural productivity is at the core of the on-going debate on how to achieve food security in Ethiopia. To this end, enhancing agricultural productivity cannot be sustained without the adoption of agricultural technologies – i.e., all kinds of improved techniques and practices which could affect the growth of agricultural outputs (Jain, Arora, and Raju 2009). Recognising the important role of agriculture technologies, the Ethiopian government has given due attention to promoting agricultural technologies. Accordingly, since the 1995 Participatory Demonstration and Extension Training System (PADETS), the government has been implementing different extension approaches to promote the adoption of improved seed, fertiliser, pesticides and improved agricultural practices. As a result, over the same period, the number of farmers using the extension service grew by 10% each year (Admassie and Ayele 2010).

Despite the huge effort from the government and the availability of promising improved technologies, the overall rate of technology adoption in the country remains low[1] (Liverpool-Tasie and Winter-Nelson 2012). The low adoption of improved agricultural technologies is among the main causes of the low agricultural productivity of small householders, when compared to their potential

CONTACT Solomon Bizuayehu Wassie sbizuayehu@gmail.com
Current affiliation for Etsehiwot Semreab Tiruneh: Kotebe Metropolitan University, Addis Ababa, Ethiopia.

productivity (Gebru 2006). To gain more insight into what drives adoption decisions and how the adoption of improved technologies can possibly increase productivity, this study examines the determinants and impact of adopting *teff* production technologies (i.e., row planting, improved seed and inorganic fertiliser) on the productivity and profitability of smallholder *teff* producers in Ethiopia.

Teff is a small grain cereal originally from Ethiopia. It is an important economic crop cultivated by 43% of small households in Ethiopia. It covers around 31% of the country's total annual acreage and 21% of its total grain production (CSA 2018). *Teff* is also among, if not the most, dominantly consumed crop in the country, with more than 50 million domestic consumers. Moreover, as *teff* is a gluten-free cereal, it has recently been getting worldwide attention (Minten et al. 2013). In response to increasing domestic and international demand, over the last two decades, the cultivated area allocated to *teff* production has increased by 60.9%. Another way total production has been increased is through the use of improved *teff* varieties and agricultural practices, and hence productivity. Yet the improvement of *teff* productivity is only marginal. In fact, the average productivity of *teff* (1.55 ton/ha) is also low compared to other cereals – i.e., maize (3.94 ton/ha), wheat (2.74 ton/ha), barley (2.157 Ton/ha) and sorghum (27.26 ton/ha) (CSA 2018). Hence, it is interesting to study the factors that drive the adoption of alternative *teff* production technologies and to what extent, if any, these alternative *teff* production technologies affect productivity and profitability.

The decision to adopt alternative production technologies is handled by individual households, and so a better understanding of the decision making related to the adoption of technology is vital to accelerate the adoption process. Therefore, while investigating the key factors that determine the simultaneous adoption of improved *teff* varieties, fertiliser and row-planting practices, this paper also evaluates the impact of alternative agricultural technologies on *teff* productivity and profitability.

The contribution of this paper to the existing literature on the adoption and impact assessment of agricultural technologies is threefold. First, although the literature in this area is large, most previous studies, with some exceptions (Zeweld et al. 2018, 2019), in Ethiopia and elsewhere (Afolami, Obayelu, and Vaughan 2015; Asfaw et al. 2012; Feleke and Zegeye 2006; Khonje et al. 2015; Liverpool-Tasie and Winter-Nelson 2012; Teklewold et al. 2013; Tesfaye, Abdissa, and Yadessa 2015; Vandercasteelen et al. 2014; Verkaart et al. 2017; Zeng et al. 2015) examined the determinants and impact of a single agricultural technology or focus on other crops. However, this study evaluates the individual and combined impact of *teff* production technology and practice (made up of improved seed, row planting and fertiliser) on *teff* productivity and profitability. This is particularly relevant because, in practice, farmers adopt more than one technology and there is interaction among the choices of alternative practices (Teklewold et al. 2013). Second, the findings of the previous studies show that the results vary across locations and among regions. Hence, location specific studies of this kind are necessary to understand the driving factors that prevent the adoption of improved *teff* production technology practices (Zeweld et al. 2018). Third, methodologically, this study employed a Multinomial Endogenous Switching Regression (MESR) model which accounts for both observable and unobservable factors in impact evaluation. Admittedly, using panel data would have an advantage in addressing the endogeneity problem, accounting for time variant factors. However, this study used cross-sectional data and attempts to complement the limitation using a rigorous regression model.

The rest of the paper is organised as follows. Section 2 provides a brief description of the data. Section 3 presents the estimation strategy and section 4 discusses the main results of the study. Section 5 concludes with policy implications.

2. Data and descriptive statistics

The study used the survey data collected by the IFPRI (International Food Policy Research Institute) in collaboration with the EDRI (Ethiopia Development Research Institute). The purpose of the survey was to get a better understanding of the *teff* value chain in Ethiopia. The data was collected during November 2012 from the Amhara and Oromia regions, which are the two biggest *teff* producing regions, contributing 43% and 55% of the total volume of the country's *teff* production, respectively (CSA 2017).

The data was collected using multistage random sampling. First, 20 districts (hereafter called by their local administrative name, *woredas*) were selected from five major *teff* producing zones in the two regions (East Gojjam, West Gojjam, East Shewa, West Shewa and South West Shewa). More specifically, all *woredas* in these zones were ranked based on their total *teff* cultivated area. Then, two *woredas* were randomly selected from the first and second half of the total *woredas* in each zone, giving 20 *woredas.* Next, all *kebeles* (i.e., the smallest administrative unit in Ethiopia) were ranked by the area allocated for *teff* production; two *kebeles* were then randomly selected from the top 50% of *teff* producing *kebeles* and one from the remaining 50% of the *teff* producing *kebeles* of each *woreda*. The *woreda* and *kebele* level data for ranking was obtained from zonal and *woreda* agriculture offices, respectively. Moreover, the Ethiopian central statistics annual survey reports were used to complement the selection process. Hence, 60 villages were randomly selected. Finally, a sampling frame was prepared by listing all *teff* producers in each *kebele* according to the area allocated for *teff* production. Then, 10 farmers were selected from the first and the second halves of the listed farmers, giving a total of 1200 *teff* producing farmers. The unit of analysis for this study is plot and some farmers have more than one plot, hence the results of this study are based on 2797 *teff* plots (Table 2). The survey used a recall method for all types of data, including price and quantity or input and output.

As shown in Table 1, this study considers the adoption of multiple alternative *teff* production technologies. Given the three technologies (fertiliser, improved seed and row planting) under consideration in different combinations of uptake, there are eight possible alternative technology choices including the control. However, as three of the alternatives each take only less than 1% of the sample population, this study is based on five alternative technology choices presented in Table 1. Specifically, these five alternative *teff* technology practices are formulated as follows: (i) the non-adopters ($F_0I_0R_0$) who do not adopt any of these technologies; (ii) fertiliser adopters ($F_1I_0R_0$) who adopt only fertiliser; (iii) fertiliser and row planting adopters ($F_1I_0R_1$); (iv) fertiliser and improved seed adopters ($F_1I_1R_0$); and (v) those who adopt all three *teff* production technologies ($F_1I_1R_1$). In fact, we acknowledge that it is not only the adoption of fertiliser, but also the rate of fertiliser applied that affects the productivity and profitability of *teff* production. However, treating fertiliser as a continuous variable will make it difficult to have a fixed number of alternative *teff* production practices to undertake comparative analysis of specific alternatives – i.e., the main interest of this study. Likewise, there may be differences among the improved varieties that farmers adopt. However, we consider all varieties that are under production for their better productivity and disease resistance (compared to the local varieties) to be improved varieties, mainly because we do not have variety-level data.

Table 2 presents descriptive statistics of the variables used in this study, by alternative *teff* production technologies including the non-adopters. The results show that both the productivity and profitability of all the technology choices are higher than that of the non-adopters. Specifically, the adoption of all three technologies together ($F_1I_1R_1$) has a 7 quintal/ha[2] yield and 9200 birr/ha profit advantage compared to the non-adopters, who adopt none of them. In this study, profit was calculated as the difference between total income from the sale of *teff* and the total cost incurred for the inputs of *teff* production, including all forms of fertiliser, seed and hired labour (i.e., for tilling, manure and organic input application, sowing, weeding, herbicide application and harvesting). Other variables can also be discussed in the same fashion. However, it is important to note that these results cannot justify the impact of technology adoption, as this could be due to other confounding factors. Hence, the variables to be used as covariates to account for confounding effects were selected carefully.

Table 1. Alternative *teff* production technologies.

Choice (j)	Adopt	Fertiliser (F)	Improved seed (I)	Row planting (R)	%
1	$F_0I_0R_0$	x	x	x	3.36
2	$F_1I_0R_0$	✓	x	x	59.38
3	$F_1I_0R_1$	✓	x	✓	7.15
4	$F_1I_1R_0$	✓	✓	x	26.59
5	$F_1I_1R_1$	✓	✓	✓	3.5

Table 2. Definition and summary of variables.

Variables	Definition and measurement of variables	$F_0I_0R_0$ (*N* = 94)	$F_1I_0R_0$ (*N*=1661)	$F_1I_0R_1$ (*N*=200)	$F_1I_1R_0$ (*N*=744)	$F_1I_1R_1$ (*N*=98)
Productivity	*Teff* productivity (quintals/ha)	8.12 (4.2)	10.2 (5.7)	10.6 (5.9)	12.5 (6.9)	15.4 (8.6)
Profit*	Profit from *teff* production (birr/ha)	5.4 (3.2)	8.1 (5.2)	7.4 (4.9)	11.8 (7.4)	14.6 (8.2)
Education	Education level of the household head (years of schooling)	4.1 (6.1)	4.5 (6.1)	6.1 (6.7)	4.5 (5.8)	8.2 (5.4)
Age	Age of the household head (years)	44.3 (13.2)	45.9 (13.3)	45.0 (11.8)	44.9 (13.7)	45.5 (11.7)
Community meetings	Frequency of participation in community meetings (number/year)	1.7 (2.5)	2.6 (3.6)	3.3 (3.6)	2.7 (3.0)	3.01 (2.6)
Extension visits	Frequency of visits by the development agent (DA) per year	1.7 (1.6)	2.5 (2.58)	3.3 (3.92)	2.9 (4.7)	4.3 (5.7)
Cooperative membership	=1 if the household head is member of cooperative, otherwise 0	0.48 (0.61)	0.61	0.67	0.71	0.91
Distance to asphalt	Walking distance from home to the nearest asphalt (hours)	4.4 (2.6)	3.4 (3.05)	3.9 (3.5)	2.3 (2.6)	2.3 (3.15)
Distance to market	Walking distance from home to the nearest output market (hours)	1.6 (1.05)	1.5 (1.15)	1.4 (1.01)	1.09 (0.75)	0.85 (0.67)
Distance to input market	Walking distance from home to the nearest input market (hours)	1.6 (1.01)	1.2 (0.96)	1.3 (1.05)	0.9 (0.75)	0.82 (0.72)
Plot distance	Walking distance from home to the plot (hours)	0.3 (0.37)	0.4 (0.3)	0.3 (0.34)	0.35 (0.27)	0.4 (0.32)
Asset	Total asset value of the household (thousands of birr)	1.5 (2.5)	3.2 (6.6)	4.1 (6.01)	3.7 (6.09)	60.2 (224)
Livestock	Number of livestock the household owned (tropical livestock unit [TLU])	4.9 (4.0)	6.2 (7.9)	6.7 (3.9)	5.9 (6.2)	7.51 (3.9)
Fertile soil	=1 if the household own fertile soil, otherwise 0	0.33	0.36	0.40	0.53	0.59
Moderate fertile soil	=1 if the household own moderate soil, otherwise 0	0.40	0.44	0.51	0.36	0.35
Infertile soil	=1 if the household own infertile soil, otherwise 0	0.28	0.19	0.09	0.11	0.06
Farm size	Total cultivation land of the household, hectare	0.58 (0.57)	0.61 (0.58)	0.5 (0.44)	0.6 (0.7)	0.6 (0.73)
Urea	Urea fertiliser used (quintal/ha)		0.6 (1.46)	0.7 (0.82)	0.99 (3.0)	1.2(1.13)
DAP	DAP fertiliser used (quintals/ha)		0.87 (1.18)	0.98 (0.7)	1.1 (0.83)	1.2 (0.82)
Herbicide	Total cost of herbicide used (birr/ha)	40.2 (60.1)	45.1 (55.9)	45.2 (70)	42.4 (55.4)	29.7 (68)

Notes: (1) the unit of analysis is plot; (2) * In calculating profit, records of farm cost and revenues are based on the recall method. The variable is measured by birr/ha but reported here in thousands for brevity. Profit refers to total income minus total cost of production, but the cost for family labour is not accounted for; (3) Reported values are mean values with their standard deviation in the parenthesis.

Selection of the variables used in this study is mainly based on previous studies (Table A2). The effect of education on technology adoption is intuitive. An educated household head, as measured by years of schooling, is likely to have better knowledge about the potential benefits of technology adoption. Likewise, community meetings, extension visits and membership in cooperatives are also hypothesised to improve access to knowledge and agricultural inputs (Zeweld et al. 2018). Community meeting refers to participation in informal institutions (e.g., *idir* and *equib*). Both *idir* and *equib* are informal institutions established among neighbours or workers to provide a rotating fund for members and to raise funds during an emergency, e.g., a death within a member's family. Farm size, number of livestock and a household's total asset-holding are proxies for the economic status of the households. Farmers with a higher economic status are more likely to invest in agricultural technology. In Ethiopia, most smallholder farmers use family labour for agricultural activities. Given this, family size is expected to have a positive and significant impact on technology adoption, particularly where technologies are labour demanding, e.g., row planting. Access to roads and markets are also expected to affect the adoption of agricultural technologies (Gebreselassie 2006). Hence, we consider distance to the nearest input market, distance to the nearest output market and distance to the nearest asphalt road in the analysis.

3. Estimation strategy

A simple approach to evaluating the impact of agricultural technology adoption is to use a dummy variable of adoption and estimate ordinary least squares. However, this approach has two limitations. First, it assumes that adopting agricultural technology is exogenously determined, while it is potentially endogenous. Second, there may be unobservable factors that explain both adoption and productivity or profitability. For instance, the most successful farm households could also be the most skilled, and hence would have done better than the others even without adopting agricultural technologies. The current study addresses these issues by estimating a MESR model.

In a multiple adoption setting, a farmer's technology choices are assumed to be based on the expected profit/gain from the adoption of a specific technology given his/her circumstances. Hence, a farmer's choice among the four alternative technologies (compared to non-adopters) and its impact on outcome variables (yield and profit) is modelled using the MESR model. The MESR model is estimated in two stages. In the first stage (adoption equation), a farmer's choice of four alternative technology practices is estimated using a multinomial logit choice model.[3] In the second stage (outcome equation), the impact of each alternative technology choice is estimated using ordinary least squares (OLS) with a selectivity correction term from the first stage (Teklewold et al. 2013).

Suppose that farmers aim to maximise their utility (U_i) – i.e., productivity or profit in our case – by comparing with an alternative package m. For the i^{th} farmer faced with J alternative technology choices, the choice of alternative technology j over any alternative package m implies that $U_{ij} > U_{im}$ for all other $m \neq j$. The expected utility of the farmer from adopting a technology package $j(U^*_{ij})$ is a latent variable determined by observed plot, household, location characteristics (Z_i) and unobserved characteristics (ε_{ij}):

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

where Z refers to observed exogenous variables defined in Table 2 and ε_{ij} is the error term. Let I be an index that indicates the choice the farmer has made, such that:

$$I = \begin{cases} 1 \text{ iff } & U^*_{i1} > \max_{m\neq j}(U^*_{im}) \text{ or } \eta_{i1} < 0 \\ \quad . & \quad . \quad\quad\quad\quad . \\ \quad . & \quad . \quad\quad\quad\quad . \\ \quad . & \quad . \quad\quad\quad\quad . \\ J \text{ iff } & U^*_{iJ} > \max_{m\neq j}(U^*_{im}) \text{ or } \eta_{iJ} < 0 \end{cases} \tag{2}$$

where η_{ij} is the expected difference in utility (productivity or profit) between alternative technology packages j and m. More formally, $\eta_{ij} = \max_{m\neq j}(U^*_{im} - (U^*_{ij}) < 0$. Hence, i^{th} farmer will adopt an alternative technology package j if (and only if) $\eta_{ij} = \max_{m\neq j}(U^*_{im} - U^*_{ij}) < 0$.

Assuming that the error terms (ε) are independent and identically distributed with Gumbel (type 1 extreme value) distributions (Green 2012), the MNL model can be specified as:

$$P_{ij} = \text{Prob}(\eta_{ij} < 0|Z_i = j) = \frac{\exp(Z_i\beta_j)}{\sum_{m=1}^{J}\exp(Z_i\beta_j)} \tag{3}$$

The second stage of the MESR model estimates the impact of adopting alternative *teff* production technology practices on the productivity and profitability of smallholder *teff* production. Suppose Y_j is an outcome variable and X_i refers to explanatory variables for each of the alternative packages. Here, Y_j is observed when alternative j is adopted. In the model specification, farmers are considered as non-adopters if they do not adopt any technology ($F_0I_0R_0$), whereas they are considered as adopters if they adopt at least one of the *teff* technology packages presented in Table 1. The outcome equation for each possible regime j is therefore given as:

$$\begin{cases} \text{Regime 1:} \quad Y_{i1} = X_i\alpha_1 + \mu_{i1} \text{ if } I = 1 \\ \quad \cdot \qquad\qquad \cdot \\ \quad \cdot \qquad\qquad \cdot \\ \quad \cdot \qquad\qquad \cdot \\ \text{Regime } J\text{:} \quad Y_{iJ} = X_i\alpha_J + \mu_{iJ} \text{ if } I = J \end{cases} \tag{4}$$

where μ' s are distributed with $E(\mu_{ij}|Z, X) = 0$ and var $(\mu_{ij}|Z, X) = \delta_j^2$.

If the ε' s and μ' s are not independent, OLS estimates in Equation (4) will be biased. Hence, consistent estimation of α_j requires the inclusion of the selection correction terms of the alternatives in Equation (4). The Dublin and McFadden model assumes that the expected value of μ_j and ε_j are linearly related, such that $E\left(\mu_{ij}\middle|\varepsilon_{1j}, \ \ldots, \varepsilon_{iJ}, Z, X\right) = \delta_j \sum_{m \neq j}^{J} \rho_j(\varepsilon_{im} - E(\varepsilon_{im}))$ where $\sum_{m \neq j}^{J} \rho = 0$ (Dubin, McFadden, and McFadden 1984). Given this assumption, the equation of the MESR in Equation (4) can be specified as:

$$\begin{cases} \text{Regime 1:} \quad Y_{i1} = X_i\alpha_1 + \sigma_1\widehat{\lambda_1} + \omega_{i1} \text{ if } I = 1 \\ \quad \cdot \qquad\qquad \cdot \\ \quad \cdot \qquad\qquad \cdot \\ \quad \cdot \qquad\qquad \cdot \\ \text{Regime } J\text{:} \quad Y_{iJ} = X_i\alpha_J + \sigma_1\widehat{\lambda_J} + \omega_{iJ} \text{ if } I = J \end{cases} \tag{5}$$

where σ_j is the covariance between ε' s and μ' s; λ_j is the inverse Mills ratio computed from the estimated probabilities in Equation (3); γ is the correlation coefficient of ε and μ; and ω' s are error terms with the expected value of zero. In the multinomial choice setting, there are $J - 1$ selection correction terms. Standard errors in Equation 5 are bootstrapped to account for possible hetroskedasticity arising from the two-stage estimation procedure (Teklewold et al. 2013).

For the model to be identified, it is important to use an exclusion restriction besides those selected by the non-linearity of the variables in Equation 1. For this purpose, we use variables that are assumed to affect the adoption decision, but do not have a direct effect on the outcome variable. The reason for this exclusion restriction is that the inverse Mills ratio is a non-linear function of the explanatory variables in the multinomial logit equation; thus the second stage equation (i.e., outcome equation) is identified because of this non-linearity. However, the non-linearity of the inverse Mills ratio is not normally tested or justified. Therefore, in order to make the source of identification clear, it is advisable to have an explanatory variable in the multinomial logit equation, which is not included in the outcome equation (Green 2012). To this end, we use distance to input and output markets as selection instruments. Following previous studies (Di Falco, Veronesi, and Yesuf 2011; Shiferaw et al. 2014), this study establishes the admissibility of these instruments by performing a simple falsification test. Accordingly, selection instruments are not jointly different from zero in the adoption equation, but they have an insignificant impact on the outcome equations. Hence, the result shows that selection instruments are valid.

The challenge with impact evaluation using non-experimental data of this kind is to estimate the counterfactual outcome – i.e., how much would the productivity or profit have been if the specific technology package j were not adopted. Following Di Falco, Veronesi, and Yesuf (2011) and Teklewold et al. (2013), the actual and counterfactual scenarios are estimated as follows:

Adopters with adoption (actually observed outcome)

$$\begin{cases} E(Y_{i2}|I=2) = X_i\alpha_2 + \sigma_2\widehat{\lambda_2} \\ \quad\quad\quad\quad . \\ \quad\quad\quad\quad . \\ \quad\quad\quad\quad . \\ E(Y_{iJ}|I=J) = X_i\alpha_J + \sigma_J\widehat{\lambda_J} \end{cases} \tag{6}$$

Adopters had they decided not to adopt (counterfactual)

$$\begin{cases} E(Y_{i1}|I=2) = X_i\alpha_1 + \sigma_1\widehat{\lambda_2} \\ \quad\quad\quad\quad . \\ \quad\quad\quad\quad . \\ \quad\quad\quad\quad . \\ E(Y_{i1}|I=J) = X_i\alpha_1 + \sigma_1\widehat{\lambda_J} \end{cases} \tag{7}$$

These expected values are then used to estimate unbiased estimates of the Average Treatment effect on the Treated (ATT). Specifically, the ATT is defined as the difference between Equations (6) and (7), for example. More formally, the ATT is given as:

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

The first term on the right-hand side of Equation (8) represents the expected change of adopters' outcome, if adopters had the same characteristics as non-adopters. The second term (λ_j) is the selection term that captures all potential differences between adopters and non-adopters which arise due to unobserved variables (Teklewold et al. 2013). Other ATT estimates are also calculated in the same fashion.

4. Results and discussion

This section presents the determinants and impact of alternative *teff* technology choices, consecutively.

4.1 Determinants of the adoption of teff *technology*

The multinomial logit model is used to investigate the determinants of *teff* production technology practices. Before embarking on estimation results, it is important to highlight the model specification and validity tests of the multinomial logit model. The result of the Wald test rejects the null hypothesis that all regression coefficients are jointly equal to zero ($Chi^2 = 2282.46$: $P > 0.00$). The Wald test result for the independence of alternative technologies also confirms that all categories (five alternative agricultural technology treatments) are distinguishable with respect to the variables in the model as indicated in Table A1.

Table 3 presents the multinomial logit model results on drivers of *teff* technology adoption. The reference or base category of the model is non-adopter ($F_0I_0R_0$) – i.e., where F, I and R refer to fertiliser, improved seed and row planting technologies; 1 indexes adoption and 0 otherwise. For example, $F_1I_0R_1$ refers to those who adopt fertiliser and row planting only. In all that follows we use these notations.

The results show one additional year of schooling increases the likelihood of adopting $F_1I_0R_1$ and $F_1I_1R_1$ by 0.2% and 0.3%, respectively, implying that educated farmers are more likely to adopt row planting technology than their counterparts. This result is consistent with our prior expectation, as education improves the ability to obtain, process and use information that is relevant for the adoption decision. While most of the previous studies obtained similar results (Afolami, Obayelu, and Vaughan 2015; Awesa 2015; Challa and Tilahun 2014; Zeweld et al. 2018), there are also others that found insignificant and negative effects (Gebreselassie 2006; Tesfaye, Abdissa, and Yadessa 2015).

Table 3. Determinants of *teff* production technology and practices (package) adoption – multinomial logit model.

	$F_1I_0R_0$		$F_1I_0R_1$		$F_1I_1R_0$		$F_1I_1R_1$	
Variables	Coef. (dy/dx)	Std Err	Coef. (dy/dx)	Std Err	Coef. (dy/dx)	Std Err	Coef. (dy/dx)	Std Err
Age	0.008 (0.001)	0.007	0.004 (−0.000)	0.009	0.001 (−0.001)	0.008	−0.001 (−0.000)	0.011
Education	0.001 (−0.003)	0.014	0.04 (0.002)**	0.017	−0.001 (−0.002)	0.015	0.08 (0.003)***	0.019
Extension visit	0.21 (0.001)***	0.053	0.27 (0.003)***	0.055	0.25 (0.006)***	0.054	0.28 (0.002)***	0.056
Community meetings	0.07 (0.005)	0.043	0.099 (0.002)**	0.047	0.049 (−0.003)	0.044	0.033 (−0.001)	0.052
Corporative membership	0.331 (0.05)*	0.180	0.490 (0.002)	0.237	0.613 (0.035)***	0.195	1.891 (0.04)***	0.411
Total land use	0.120 (−0.005)	0.085	0.168 (0.002)	0.093	0.168 (0.008)*	0.089	0.200 (0.002)**	0.101
Soil fertility (reference = fertile)								
Medium fertility	0.138 (0.085)	0.202	−0.195 (0.015)	0.249	−0.374 (−0.089)*	0.211	−0.393 (−0.011)	0.310
Infertile	−0.205 (0.15)	0.230	−1.09 (−0.03)***	0.351	−0.99 (−0.12)***	0.255	−1.59 (−0.03)***	0.484
Livestock (TUL)	−0.029 (0.002)	0.037	−0.044 (−0.001)	0.038	−0.048 (−0.003)	0.039	−0.053 (−0.001)	0.042
Distance to the plot	0.548 (0.04)	0.533	0.189 (−0.02)	0.614	0.449 (−0.01)	0.533	0.907 (0.01)	0.584
Asset value	0.12 (0.001)**	0.059	0.15m (0.002)**	0.061	0.12 (0.002)**	0.06	0.17 (0.001)***	0.067
Distance to input market	−0.29 (−0.01)***	0.077	0.005 (0.017)	0.098	−0.37 (−0.02)***	0.107	−0.12 (0.005)	0.199
Distance to output market	0.115 (0.07)	0.089	−0.03 (−0.001)	0.114	−0.25 (−0.056)**	0.103	−0.48 (−0.013)**	0.212
Distance to asphalt road	−0.06 (0.01)***	0.021	−0.004 (0.005)	0.029	−0.18 (−0.02)***	0.032	−0.12 (−0.001)*	0.064
Constant	1.068***	0.395	−1.69***	0.553	1.663***	0.419	−2.580***	0.666

Notes: ***, ** and * refer to 1%, 5% and 10% significant levels; dy/dx refers to the marginal effect.

The adoption of new technology can be affected by the level of awareness and knowledge about technologies (Mwangi and Kariuki 2015; Zeweld et al. 2017). In this regard, the current study considers distance to the input and output markets, access to extension services and community meetings as proxies for access to and knowledge about the available technologies – i.e., improved seed, fertiliser and row planting. In the Ethiopian agricultural system, development agents (DAs) are grassroots-level extension agents who are mainly responsible for supporting farmers to adopt technologies and practices. Hence, DAs are the main source of information about the availability and importance of the improved technologies – i.e., both inputs and agronomic practices – for farmers (Gebru 2006). In line with this, the result of the study shows that the one more unit increase in the frequency of extension visits is associated with a 1%, 3%, 6% and 2% increase in the likelihood of adopting $F_1I_0R_0$, $F_1I_0R_1$, $F_1I_1R_0$ and $F_1I_1R_1$, respectively. This result is parallel with the findings of previous studies (Awesa 2015; Feleke and Zegeye 2006; Mekonnen 2017).

Community meetings, i.e., informal institutions where farmers gather to exchange ideas in their daily lives, are also an important source of information about the potential benefits and associated costs of improved agricultural inputs, technologies and agronomic practices. Hence, informal sources of information (like community meetings) will have a role in the adoption decision. The results of this study also show that the frequency of attending community meetings has a positive and significant (2% more likely) impact on the $F_1I_0R_1$ technology adoption decision. The result also supports the argument by Mwangi and Kariuki (2015) which notes that community meetings increase social capital, trust and information exchange about new technology. Likewise, cooperative membership was found to have a positive and significant impact on the adoption of *teff* production technology. Specifically, being a member of a cooperative increases the probability of adopting $F_1I_0R_0$, $F_1I_1R_0$ and $F_1I_1R_1$ by 5%, 3.5% and 4%, respectively. However, cooperative membership has no significant effect on $F_1I_0R_1$, possibly because cooperatives mainly focus on input supply rather than promoting improved agricultural practices like row planting. Intuitively, participation in cooperatives may directly influence technology adoption as it provides access to agricultural inputs, credit and information (Abebaw and Haile 2013; Kolade and Harpham 2014). Moreover, external financial agencies and governments prefer to deal with groups rather than individual farmers in the payment of loans and distribution of subsidised inputs.

Distance to the main road and distance to the input market have a negative and significant effect on the adoption of $F_1I_0R_0$ and $F_1I_1R_0$. Distance to the output market affects the adoption of $F_1I_1R_0$ and $F_1I_1R_1$ technologies negatively and significantly. For example, one more unit increase in distance from an output market is associated with a 5.6% and 1.3% decrease in the probability of adopting $F_1I_1R_0$ and $F_1I_1R_1$. Overall, the results suggest that access to the market and the main road make a considerable contribution to *teff* technology adoption. One possible explanation for this can be because farmers with better access to the market and the main road may buy agricultural inputs and sell outputs on time and at a reasonable price (Gebru 2006; Vandercasteelen et al. 2017). Our result is consistent with Hailu et al. (2014) and Vandercasteelen et al. (2017), but contrary to Weyessa (2014).

In developing countries like Ethiopia where there is limited access to credit,[4] asset ownership will solve the liquidity constraints associated with the adoption of agricultural technologies. Briefly, farmers with better asset holdings are likely to be rich enough to buy inputs or they have assets to sell to solve their liquidity constraints (Kaliba et al. 2018). In line with this, the results show that a thousand birr increment on asset holding increases the probability of adopting $F_1I_0R_0$, $F_1I_0R_1$, $F_1I_1R_0$ and $F_1I_1R_1$ *teff* production technologies by 0.1%, 0.2%, 0.2% and 0.1% respectively. Likewise, a hectare increment in land increases the likelihood of adopting $F_1I_1R_0$ by 0.8% and $F_1I_1R_1$ by 0.2%. A possible explanation for this can be the economies of scale from investing in agricultural technology. Similarly, as technology adoption is relatively costly, farmers tend to adopt the technologies in their fertile plots where they expect higher yield. Accordingly, our result shows that the adoption of *teff* technology practices ($F_1I_0R_1$, $F_1I_1R_0$ and $F_1I_1R_1$) is higher on the plots with better soil fertility.

4.2 Impact of teff technology adoption on productivity and profit

We used the MESR model to examine the impact of alternative *teff* technologies on the productivity and profitability of smallholder *teff* production. The model result shows that the self-selection problem is apparent in the data. Specifically, the Mills ratio values are significant, implying that using the MESR is appropriate (Di Falco and Veronesi 2013). The validity of IV variables was also checked using a falsification test. The results indicate that the IV variables are valid for both the productivity and profitability equations. Specifically, the IV variables (i.e., distance to input and output markets) significantly affect the selection equations, but have no detectable effect on the outcome equations.

Table 4 presents the estimated conditional average treatment effect of *teff* technology adoption on productivity. The true average impact of *teff* technology adoption on productivity is estimated by comparing the actual productivity with the respective counterfactual – i.e., what they would have got if they had decided not to adopt (referred to as "non-adopters" in Table 4). The first panel of Table 4 shows that adoption of $F_1I_0R_0$ (fertiliser only) has a positive and significant impact on yield, compared to non-adopters ($F_0I_0R_0$). Explicitly, the adoption of $F_1I_0R_0$ will increase yield by 2.16 quintals/ha. The second panel of Table 4 shows that adoption of $F_1I_0R_1$ will have a 2.13 quintals/ha increment on yield compared to non-adopters. Likewise, full technology adoption ($F_1I_1R_1$) can increase productivity by nearly twofold, compared to non-adopters ($F_0I_0R_0$). However, there is no detectable difference between $F_1I_0R_1$ and its counterfactual – i.e., if they had not adopted row planting ($F_1I_0R_0$). Other estimations can be interpreted in a similar fashion.

Overall, the results show that adopters of any combination of *teff* production technologies and practices have higher productivity than they would have had if they were non-adopters. The results show that full technology adopters are the most productive compared to all alternative *teff* production technologies (i.e., single and mixed technology adopters). The highest productivity is obtained when the farmers adopt the full package (15.64 quintals/ha) followed by $F_1I_1R_0$ (12.46 quintal/ha). The lowest productivity is obtained when farmers adopt the single technology of fertiliser only. The second panel of Table 2 shows that there is no detectable difference in productivity between adopting fertiliser ($F_1I_0R_0$) and fertiliser and row planting technology ($F_1I_0R_1$) – i.e., without improved seed. On the other hand, as shown in the third panel of Table 4, $F_1I_1R_0$ adopters would have yielded 0.92 quintals/ha less if they had dropped improved seed and adopted row planting. In this regard, previous empirical studies also found a positive impact of agricultural technologies on productivity (Gebru 2006; Kassie et al. 2015; Teklewold et al. 2013; Tesfaye, Abdissa, and Yadessa 2015; Tesfaye, Bedada, and Mesay 2016; Vandercasteelen et al. 2017).

Table 5 presents the estimated impact of adopting *teff* production technology and practices on profitability. The first panel of Table 5 shows that $F_1I_0R_0$ adopters would have had 2612.24 birr/ha

Table 4. Impact of *teff* technology adoption on productivity (quintals/ha).

		Subsamples for treatment groups			
Non-adopters	Decision stage	(1) $\mathbf{F_1I_0R_0}$	(2) $\mathbf{F_1I_0R_1}$	(3) $\mathbf{F_1I_1R_0}$	(4) $\mathbf{F_1I_1R_1}$
$F_0I_0R_0$	To adopt	10.21	10.65	12.46	15.64
	Not to adopt	8.04	8.53	8.17	8.62
	TT	2.16***	2.128***	4.28***	7.021***
$F_1I_0R_0$	To adopt	-	10.65	12.46	15.64
	Not to adopt	-	10.64	10.57	11.55
	TT	-	0.01	1.88**	4.09***
$F_1I_0R_1$	To adopt	-	-	12.46	15.64
	Not to adopt	-	-	11.53	12.93
	TT	-	-	0.92**	2.71***
$F_1I_1R_0$	To adopt	-	-	-	15.64
	Not to adopt	-	-	-	13.70
	TT	-	-	-	1.94**

Note: *** and ** refer to 1% and 5% significant level, respectively.

Table 5. Impact of *teff* technology adoption on profit (birr/ha).

Non-adopters	Decision stage	Subsamples for treatment groups (1) $F_1I_0R_0$	(2) $F_1I_0R_1$	(3) $F_1I_1R_0$	(4) $F_1I_1R_1$
$F_0I_0R_0$	To adopt	8080.49	7497.43	11844.33	14880.05
	Not to adopt	5339.13	5832.06	5196.21	5696.06
	TT	2741.36***	1665.37***	6648.12***	9183.99***
$F_1I_0R_0$	To adopt	-	7497.43	11844.33	14880.05
	Not to adopt	-	8393.71	8281.31	9197.50
	TT	-	−896.27**	3563.02***	5682.54***
$F_1I_0R_1$	To adopt	-	-	11844.33	14880.05
	Not to adopt	-	-	7572.81	9014.61
	TT	-	-	4271.53***	5865.45***
$F_1I_1R_0$	To adopt	-	-	-	14880.05
	Not to adopt	-	-	-	12718.25
	TT	-	-	-	2161.81***

Note: *** and ** refer to 1% and 5% significant level, respectively.

less profit had they not adopted fertiliser. Similarly, the profitability of $F_1I_1R_1$, $F_1I_1R_0$ and$F_1I_0R_1$ adopters would have decreased by 9183.99, 6648.12 and 1665.37 birr/ha if they had become non-adopters. Hence, adopting one or more of the available technologies and practices makes farmers more profitable than being non-adopters. The result also shows that $F_1I_0R_1$ adopters would have gained 896.27 birr/ha more profit if they had not only adopted fertiliser ($F_1I_1R_0$). This has an important implication for row planting technology adoption – i.e., row-planting technology is profitable only when used with improved seed. This could be mainly because row-planting technology is costly and hence will be profitable when applied with improved seeds that have a higher productivity potential, under some suitable conditions. The result in the fourth panel of Table 5 further supports this argument. Full technology adopters ($F_1I_1R_1$) would have 2161.81 birr/ha less profit if they did not adopt only row-planting technology ($F_1I_1R_0$). This result is similar to that of Vandercasteelen et al. (2014), who found that adoption of row planting improved productivity but not necessarily profitability, mainly because of the associated higher labour cost. On the other hand, when farmers adopt a combination of less costly technologies like fertiliser with improved seed, they consistently get higher profit. Specifically, adoption of $F_1I_1R_0$ gives a 6648.12, 3563.02 and 4271.53 birr/ha higher profit compared to what they would have had if they were non-adopters ($F_0I_0R_0$), or even adopters of $F_1I_0R_0$ and $F_1I_0R_1$ respectively.

5. Conclusion and recommendation

Despite the huge effort from the government towards the adoption of *teff* technology and improving its productivity in Ethiopia, average productivity remains low compared to that of other cereals. It is increasingly accepted that technology adoption will help smallholder farmers to increase productivity and hence improve their livelihoods. In this study, we have empirically investigated the determinants and impact of alternative *teff* production technologies and practices in the Ethiopian context. Admittedly, there are many empirical studies on the adoption and impact of agricultural technologies in Ethiopia and elsewhere. However, prior research focuses on the impact of a single agricultural technology or practice, hence, the information on simultaneous adoption of multiple agriculture technologies (i.e., fertiliser, improved seed and row planting) simultaneously, and their impact, is scarce.

This study therefore employed a multinomial endogenous switching regression model and examined the adoption of alternative *teff* production technologies and their impact on productivity and profit. The multinomial logit model result revealed that the agricultural technology adoption decision is influenced by observable plot and household level characteristics and institutional factors. More specifically, the decision to adopt agricultural technology is positively related to education, farm size, extension visits, community meetings and asset ownership. On the contrary, distance to input and output markets have a negative and significant effect on the adoption of alternative *teff* production technology and practices. These results can have important implications for the path forward to improve the adoption of alternative agricultural production technologies. For example, the government should use informal sources of information such as community meetings as an alternative way to increase knowledge about agricultural technologies. The study also shows that distance to input and output markets negatively contributes to technology adoption decisions. Furthermore, asset ownership has a positive and significant effect on technology adoption decisions. With regard to this last finding, increasing access to financial institutions would probably help to resolve the liquidity constraints for asset ownership, and hence increase technology adoption.

The second stage of the MESR model result presents the impact of alternative *teff* technologies on smallholder productivity and profitability in Ethiopia. The result revealed that adopting any of the alternative technology makes farmers more productive and profitable compared to non-adopters. For example, for non-adopters, the adoption of fertiliser and improved seed can increase productivity by nearly by 100%. Likewise, full technology adoption ($F_1I_1R_1$) can increase productivity and profitability by nearly twofold, compared to that of non-adopters ($F_0I_0R_0$). On the other hand, $F_1I_0R_1$ (fertiliser and row planting) adopters have 40% less profit than fertiliser-only adopters ($F_1I_0R_0$), possibly because row planting technology is labour demanding and hence costly to apply with the local varieties which are less productive. Likewise, there is no significant productivity difference between $F_1I_0R_0$ (fertiliser only) and $F_1I_0R_1$ (fertiliser and row planting) adopters. These results suggest that row-planting technology has to be adopted together with improved seed technology. The results further show that full technology adoption – i.e., simultaneous adoption of fertiliser, improved seed and row planting – makes the farmer more productive and profitable than adopting any other alternative technologies. These results suggest that the government and other stakeholders should promote the adoption of full technology (an integrated approach with several practices applied) to increase the productivity and profitability of smallholder farmers.

Notes

1. Inorganic fertiliser and improved seeds were applied only on 56.76% and 13% of the total cultivated land covered by cereals (CSA 2018).
2. Quintal is a unit of weight equal to 100 kg.
3. When the independence of irrelevant alternative (IIA) choice assumption is fulfilled, multinomial logit model is preferred over multinomial probit model for its stability and simplicity (Kropko 2008). Model specifications in this study are adopted from Teklewold et al. (2013).
4. More than 60% of the adults have no access to banking services in Ethiopia (Demirguc-Kunt et al. 2018).

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ORCID

Solomon Bizuayehu Wassie http://orcid.org/0000-0002-5200-8851

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Appendix

Table A1. Alternative technologies independence test.

Categories	Tested	chi2	*P* > chi2
$F_0I_0R_0$	$F_1I_0R_0$	83.794	0.00
$F_0I_0R_0$	$F_1I_0R_1$	75.709	0.00
$F_0I_0R_0$	$F_1I_1R_0$	193.468	0.00
$F_0I_0R_0$	$F_1I_1R_1$	127.507	0.00
$F_1I_0R_0$	$F_1I_0R_1$	93.107	0.00
$F_1I_0R_0$	$F_1I_1R_0$	182.876	0.00
$F_1I_0R_0$	$F_1I_1R_1$	126.208	0.00
$F_1I_0R_1$	$F_1I_1R_0$	136.775	0.00
$F_1I_0R_0$	$F_1I_1R_1$	48.835	0.00
$F_1I_1R_0$	$F_1I_1R_1$	84.602	0.00

Table A2. Summary of previous empirical studies.

No.	Author/s, year	Country	Data type	Methodology	Treatment variable	Result	
						Determinants of technology	Outcome indicators
1	Afolami, Obayelu, and Vaughan (2015)	Nigeria	Cross-sectional data	Logit regression	Improved variety	Use of radio (+), farming experience (+), education (+)	Income (+), consumption expenditure (+)
2	Asfaw et al. (2012)	Ethiopia and Tanzania	Cross-sectional	Endogenous switching regression models	Improved variety		Household welfare (+)
3	Challa and Tilahun (2014)	Ethiopia	Cross-sectional data	Probit model and the PSM method		Education (+), credit accessibility (+), attitudes of farmers towards the fairness of cost of inputs (+) and having off-farm income (+), farm size (-)	Income (+), productivity (+)
4	Feleke and Zegeye (2006)	Ethiopia	Cross-sectional data	Logistic regression	Improved variety	Extension service (+), credit service (+), distance to the market (-), education (+), labour (+)	
6	Gebru (2006)	Ethiopia	Cross-sectional data	Logit model and Cobb Douglas function	Agricultural inputs	Larger farm size (+), own large number of oxen (+), had access to credit (+) and located near to input delivery institutions (+)	Productivity (+)
7	Hailu, Abrha, and Weldegiorgis (2014)	Northern Ethiopia	Cross-sectional data	Probit model and OLS	Chemical fertiliser and improved variety	Gender (+), land ownership (+), irrigation use (+), access to credit (+), contact with extinction agent (+), participation on off-farm activity (+), plot distance from the homestead (-) and distance to the nearest market (-).	Income (+)
8	Kassie et al. (2015)	Malawi	Cross-sectional	MESR model	Improved maize varieties, intercropping and rotation practices		Income (+)
9	Khonje et al. (2015)	Zambia	Cross-sectional data	PSM and endogenous switching regression models	Improved variety		Income (+), consumption expenditure (+), food security (+)
10	Liverpool-Tasie and Winter-Nelson (2012)	Ethiopia	Cross-sectional data	Probit	Irrigation	Livestock (+), asset (+), distance to road (-), farm size (-), friend adopters (+)	
11	Mekonnen (2017)	Ethiopia	Panel data	PSM and the probit model	Improved agricultural	Education (+), farm size (+), labour (+), credit access (+), quality of land (+) and livestock asset (+)	Income (+)
12	Minten et al. (2013)	Ethiopia	Cross-sectional data	Double- hurdle model and PSM	Improved variety	Daily wage rate (+), distance to all-weather road (+), the slope of land (+), distance to the city (-) and transportation cost (-)	Productivity (+)
13	Sebsibie, Asmare, and Endalkachew (2014)	*Amhara,* Ethiopia	Cross-sectional	Double-hurdle model	Chemical fertiliser		Household welfare (+)

(*Continued*)

Table A2. Continued.

No.	Author/s, year	Country	Data type	Methodology	Treatment variable	Result	
14	Teklewold et al. (2013)	Ethiopia	Cross-sectional data	MESR model	Cropping system diversity, conservation tillage and modern seed adoption	Market access (+), wealth (+), age (+), spouse's education (+), the farmer's expectations of government support in case of crop failure (-), and confidence in the skill of public extension agents (+)	Income (+) and productive(+)
15	Tesfaye, Abdissa, and Yadessa (2015)	Ethiopia	Cross-sectional data	Dominance and profitability analysis	Profit from different *Teff* planting methods		Row planting profit (+), transplanting profit (+)
16	Tesfaye, Bedada, and Mesay (2016)	Ethiopia	Cross-sectional data	PSM and the Probit model	Improved wheat	Education (-), gender (+), wheat rust disease (+)	Productivity (+) and income (+)
17	Vandercasteelen et al. (2014)	Ethiopia	Cross-sectional data	A randomised control trial method, OLS	Row planting		Productivity (+)
18	Verkaart et al. (2017)	Ethiopia	Panel data	Double-hurdle model	Improved variety		Income (+)
19	Zeng et al. (2015)	Ethiopia	Cross-sectional data	2SLS, Probit-2SLS	Improved variety		Poverty headcount ratio (-)

Source: Authors' review.