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# Impact of Coffee Technologies: A Multinomial Endogenous Switching Regression Model

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**Abstract:** Sector of agriculture plays a significant role in Ethiopian economy. Ethiopia has huge potential to increase coffee production as it endowed with suitable elevation, temperature, and soil fertility, indigenous quality plantation materials, and sufficient rainfall in coffee growing belts of the country. The combination of coffee technologies adoption has a significant effect on coffee productivity. The study was aim at identifying the impact of coffee Varity and coffee land management practice on annual coffee yield in south western Ethiopia. This study develops a multinomial endogenous switching regression model of farmers' choice of combination of coffee technologies and impacts on coffee technologies. Both qualitative and quantitative data collected in multistage sampling techniques. Data was collected from both primary and secondary data sources. 196 sampled households from three woreda in the zone and 430 plots of 196 farmers household is considered in the survey. Two primary results were found. First, adoption rate and intensity of improved coffee variety is greater than adoption of coffee management practice. Secondly adoption of coffee technologies determined by much institutional, resource and other related factor. This implies that policy makers and other stakeholders promoting a combination of technologies can enhance coffee yield through reducing production costs and decreasing coffee vulnerability to disease.

**Keywords:** Coffee Technologies, Adoption, Multivariate Probit Model

## 1. Introduction

### *1.1. Background of the Study*

Agriculture is one of the central fields which shape the socio-economic development of any country (Mohamad and Gombe, 2017). Therefore, the life of all human beings is heavily dependent on agricultural products and its importance is going to increase day to day. Consequently, Agriculture has long been the backbone of Africa economy and the potential sources of economic growth in spite of all its weaknesses [1].

It plays a central role in increasing food availability and incomes, supporting livelihoods and contributing to the overall economy and a key factor to improve food and nutrition security. Ethiopia's economy is dependent on rain-fed agriculture. The sector contributes about 46.3% of the total gross domestic product (GDP), 60% of exports, and 80% of total employment Smallholders drive their benefits either in cash from the sale of a product or through their consumption of agricultural products. The production system constitutes crop and livestock rearing accounting for 70%, and the pastoral production system accounts for 30%.

Ethiopia has huge potential to increase coffee production as it endowed with suitable elevation, temperature, and soil fertility, indigenous quality plantation materials, and sufficient rainfall in coffee growing belts of the country. Coffee is a shade-loving tree. It grows well under the large indigenous trees such as the Cordia Abyssinica and the Acacia species, in two regions of the country Oromiya and southern nation nationality and people regional state. In the country smallholder farmers on less than two hectares of land produces and supply Ninety-five percent of Ethiopia's coffee produces, while the remaining five percent grown on modern commercial farms [18, 20]. In Ethiopia, 764863.16 ha of land was allocated for coffee production and 494574.36 tones were obtained with average productivity of 0.64 tones ha-1 in 2018/19 Meher Season from which 30% of the total production belongs to South Nation Nationalities and Peoples Regional State (SNNPR). From top 25 coffee producing districts in Ethiopia, Oromia dominates with 18 coffee producing districts and the remaining top coffee producing districts are located in South Nations, Nationalities and Peoples Regional State. Coffee land coverage and dependency of smallholder farmers on coffee is high especially in southwest Ethiopia. [8] found that the share of coffee income from total income in coffee producing districts of Jimma zone is 77%. On other hands, share of land allocated to coffee crop in these areas is more than 69%.

More than 120 Ethiopian Coffee exporters participated in processing and exporting coffee to all destination of the world. Among these export companies 95% are private companies 5% are Coffee growing farmers' cooperative unions and two of them are government enterprises In 2010/11 the top five coffee export destinations for the country are Germany, United stat of America, Saudi Arabia, Belgium and Italy. The country produces almost 200,000 metric tons of coffee every year. 95% of the coffee is produced in the forest area and is claimed to be organic. A major part of the Ethiopian coffee is exported in green coffee beans form, to the Rest of the World.

This study was designed to explore factors limiting adoption of coffee production technologies, constraints related to coffee production, relative benefits of coffee technologies on coffee annual yield among adopters of the improved technologies. The result of the study could be helpful for coffee related biological and physiological researchers, and policy makers.

In general, different packages of coffee production, protection and processing technologies have been promoted to beneficiaries since long period of time. Several institutions were also involved in disseminating these technologies through various extension approaches. However, there is no adequate information on demand for new coffee production and processing technologies and adoption by smallholder farmers in different agro-ecologies of Jimma zone. Moreover, the impacts of the technologies on the coffee annual yield are not adequately addressed and documented for different categories of households. Therefore, this study is focused to fill these gaps and generate information on the status of demand, adoption and impacts of coffee production technologies at smallholder levels.

### *1.2. Statement of the Problem*

Ethiopia has not yet fully exploited its position as the producer of some of the best coffees in the world. Coffee sector is highly dependent on international prices and affected by the structure and workings of the world coffee market. Ethiopia is one of the countries mostly affected by the crisis in world coffee prices (Cerda et al 2017). The productivity of coffee is very less, not more than 6 qt/ha. To improve the productivity of coffee and enhance farmers' on-farm incomes, the national agricultural research system has generated and disseminated more than 30 improved coffee varieties and associated production packages. These technologies were promoted and disseminated to coffee producers through various mechanisms, such as demonstrations, seed distribution and farmer-to-farmer technology exchange mechanisms. Various development actors have also participated in the promotion and dissemination of coffee production technologies since the last decades. Some of the institutes engaged in dissemination of coffee production technologies included Jima Agricultural Research Center, Offices of Agriculture, and another institute.

Coffee diseases cause considerable losses when not treated. According to [5], 57% yield loss was observed by the infection of disease-causing organisms on coffee crop also reported that the most economically important pathogenic coffee diseases are coffee berry disease (CBD), coffee wilt disease (CWD) and coffee leaf rust (CLR), and physiological disorder like coffee branch die back is caused by pseudomonas syringe and non-pathogenic agents. Similarly, CBD and branch dieback were causing high yield loss of coffee production. In the same way, insect pests such as Anthestia bug and coffee blotch miner are the major ones causing considerable damage. The assessment carried out in Eastern Ethiopia indicated that diseases and insect pests are causing considerable crop losses. CBD is major disease observed while CWD was considered as minor on few farmers' coffee farms. Similarly, major insect pest that affects coffee production in Eastern Ethiopia were coffee stem borer and coffee berry borer. On the other hand, insect pests such as coffee trips, green scale and coffee cushion scale were reported as important coffee production constraints in the country [11]. Low production and productivity, which are mainly associated with poor adoption of recommended coffee technologies, were among the major problems. Adoption of improved technologies is one of the most promising ways to increase productivity and production in Ethiopia. Farmers are facing challenges, including increasingly erratic rainfall, rising temperatures, poor management of coffee trees, fluctuation of coffee prices and degradation of soil, that are adversely affecting their income opportunities the country's coffee production. Coffee production and productivity was used to develop appropriate technology for improvement and inform policy makers to understand the gap. However, the adoption and dissemination of these technologies is constrained by various factors. Different studies have been conducted on adoption of coffee technology in Ethiopia [7, 9, 16, 14]. Most of this research focus only on factor affecting adoption of coffee variety and few research was conducted on the adoption of the coffee technologies and agronomic practice impact on yield of coffee this research is designed to determine adoption rate of improved coffee varieties and associated packages of technologies. Moreover, the study will explore factors limiting adoption of coffee production technologies.

However, this study will examine the adoption level coffee Varity and agronomic practice also evaluate the impact of coffee variety and coffee agronomic practice and their impact in coffee yield. Thus, this study will fill the existing knowledge gap by assessing adoption and impact of coffee technology and impact on yield in Jimma zone taking with Mana, Gomma and Limu kosa district as a case study.

The findings of the study will help for coffee breeders to understand the key factors which determine farmers' preferences to improved coffee varieties. In their future breeding program, the coffee breeders will consider the influencing factors and merits which the farmers expect to exist on improved coffee varieties. In addition to this, extension service providers will get adequate information on the extent to which technology promotion and extension service provision mechanisms utilized so far worked or not. It will also provide information on the types of technology dissemination mechanisms which were effective in reach out to the farmers. Policy makers will also get information on the social, economic and environmental factors which determined the adoption of coffee production technologies, to identify constraints and opportunities related to coffee production, relative benefits of coffee technologies on coffee annual yield among adopters of the improved technologies. The result of the study could be helpful for coffee related biological and physiological researchers, policy makers and finally for the farmers.

### *1.3. Description of the Study Area*

Jimma is a zone in Oromia State of Ethiopia. It is named after former Kingdom of Jimma, which was absorbed into the former province of Kaffa in 1932. Jimma is bordered on the south by the Southern Nations, Nationalities and Peoples Region, the northwest by Illubabor Zone, on the north by East Welega Zone and on the northeast by West Shewa Zone; part of the boundary with East Shewa Zone is defined by the Gibe River. The highest point in this zone is Mount Maigudo (2,386 m). Towns and cities in Jimma include Agaro, Limmu Inariya and Saqqa. The town of Jimma was separated from Jimma Zone and is a special zone now. Based on the 2007 Census conducted by the CSA, this Zone has a total population of 2,486,155, an increase of 26.76% over the 1994 census, of whom 1,250,527 are men and 1,235,628 women; with an area of 15,568.58 square kilometers, Jimma has a population density of 159.69. While 137,668 or 11.31% are urban inhabitants, a further 858 or 0.03% are pastoralists. A total of 521,506 households were counted in this Zone, which results in an average of 4.77 persons to a household, and 500,374 housing units. It has a latitude and longitude of 7°40′N 36°50′E. Prior to the 2007 census.

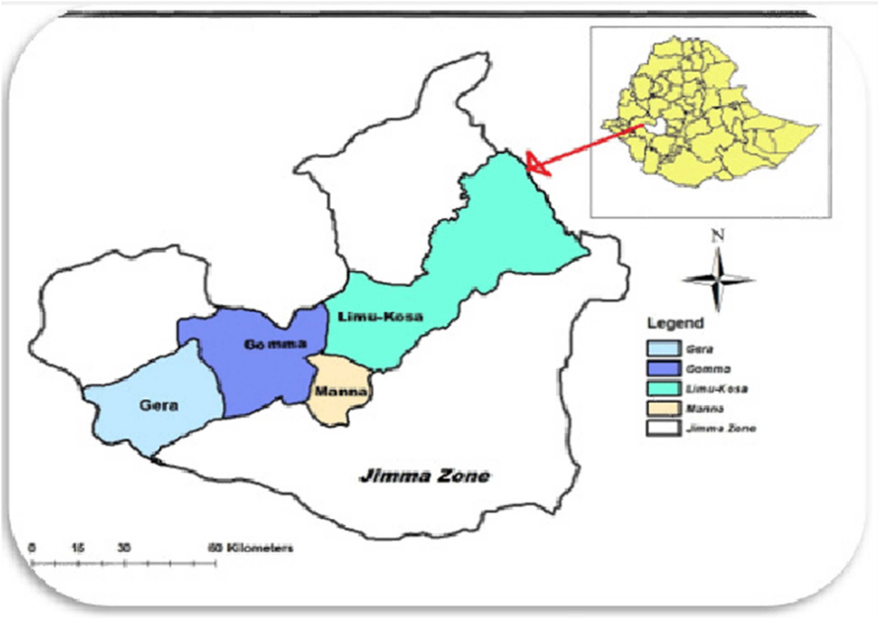


***Figure 1.*** *Map of the study area.*

## 2. Methods of Data Collection

The study was based on the cross-sectional data set. It was collected using both qualitative and quantitative data collection tools. The quantitative data collection tool was used to collect data from representative households through administrating an independent structure questionnaire (both close and open-ended questionnaire) to the producer personal interview. Before the Formal data collection structured questionnaires were pretested on the ground and modified accordingly. As far as the qualitative data collection tools are concerned, they were key informant interview, individual in-depth interview and focus group discussion. FGD was made with coffee producers. Key informant was purposively selected and interviewed who works in the area related to coffee production.

### *2.1. Sampling Techniques*

Both primary and secondary data was collected and used to investigate the problems. Primary data like farmers specific characteristics resource factor and other data collected service provided by the experts and other were collected from the respondents by using interview with questionnaire and the survey were held by using designed CSPro software and secondary data were collected from different information sources like experts in the zone and district, previous studies and others.

### *2.2. Sample Size*

The dataset used for this study is based on a farm household survey conducted in Ethiopia during October–December 2014 by the Ethiopian Institute of Agricultural Research (EIAR) in collaboration with the EU. A multistage sampling procedure was employed to select peasant district from the zone. First, based on their coffee production potential, three or four kebele from each district were selected then based on proportionate random sampling after selecting a potential district by a simple probability sampling techniques 12 to 16 household in each kebele were selected.

### *2.3. Data Analysis*

#### *2.3.1. Descriptive Analysis*

Descriptive statistics such as means, percentage, and standard deviation were computed to explain different demographic and socioeconomic characteristics of the households.

#### *2.3.2. Econometric Analysis*

From the expected utility theory farmers under uncertain condition aim at maximizing the expected utility. From this theory it is assumed that farmers aim to maximize their expected profit, Ui, by comparing the profit provided by m alternative packages. The requirement for farmer i to choose any package, j, over any alternative package, m, is that $U_{ij} > U_{im}$ m≠j or equivalently $\Delta U_{im} = U_{ij} - U_{im} > 0$ m≠j The expected profit of $U_{ij}^*$ that the farmer derives from the adoption of package j is a latent variable determined by observed household, plot and location characteristics $X_i$ and unobserved characteristics $\mathcal{E}_i$:

$$U_{ij} = X_i\beta_j + \mathcal{E}_i \tag{1}$$

where $X_i$ is observed exogenous variables (household, plot and location characteristics) and $\mathcal{E}_i$ is unobserved characteristics. Let *(I)* be an index that denotes the farmer's choice of package, such that:

$$I = \begin{cases} 1 \text{ iff } U_{i1} > \underset{\mathrm{m} \neq \mathrm{j}}{\max}(U_{im}^*) \, or \, \eta_{i1} < 0 \\ \cdot \\ \cdot \\ \cdot \\ \text{J iff 1: } U_{ij} > \underset{\mathrm{m} \neq \mathrm{j}}{\max}(U_{im}^*) \, or \, \eta_{iJ} < 0 \end{cases} \tag{2}$$

Where $\eta_{ij} = max_{\mathrm{m}\neq\mathrm{j}}\left(U_{im}^* - U_{ij}^*\right) < 0$ (Bourguignon et al., 2007). Eq. (2) implies that the ith farmer will adopt package j to maximize his expected profit if package j provides greater expected profit than any other package m ≠ j that is

$$\eta_{iJ} = max_{\mathrm{m}\neq\mathrm{j}}\left(U_{im}^* - U_{ij}^*\right) > 0.$$

Multinomial logistic regression is often considered an attractive analysis because; it does not assume normality, linearity, or homoscedasticity. A more powerful alternative to multinomial logistic regression is discriminant function analysis which requires these assumptions are met. Indeed, multinomial logistic regression is used more frequently than discriminant function analysis because the analysis does not have such assumptions. Multinomial logistic regression does have assumptions, such as the assumption of independence among the dependent variable choices. This assumption states that the choice of or membership in one category is not related to the choice or membership of another category (i.e., the dependent variable). The assumption of independence can be tested with the Hausman-McFadden test. Furthermore, multinomial logistic regression also assumes non-perfect separation. If the groups of the outcome variable are perfectly separated by the predictor(s), then unrealistic coefficients will be estimated and effect sizes will be greatly exaggerated [12].

Assuming that $\mathcal{E}$ are identically and independently Gumbel distributed, the probability that farmer i with characteristics X will choose package j can be specified by a multinomial logit model (McFadden, 1973):

$$P_{ij} = \Pr(\eta_{ij} < 0|X_i = \frac{\exp(X_i\beta_j)}{\sum_{m\neq j}^{J}\exp(X_i\beta_m)} \tag{3}$$

### *2.4. Impact of Coffee Technology on Coffee Annual Yield*

To analyze the impact of coffee technologies adoption on annual coffee yield, the observable and unobservable characteristics of the adopters and non-adopters must be captured. However, most impact assessment techniques using non-experimental data fail to capture both observable and unobservable characteristics that affect adoption and outcome variables [14]. For instance, instrumental variables capture only unobserved heterogeneity, but the assumption is that the parallel shift of outcome variables can be considered as a treatment effect [17]. In contrast, using regression models to analyze the impact of a given technology using pooled samples of adopters and non-adopters might be inappropriate since it gives a similar effect on both groups [17].

Propensity score matching (PSM) was not used in this study since it does not control the unobservable characteristics. A methodological approach that overcomes these limitations of different impact evaluation methods is the ESR model, which is the most used method to analyze the impact of a given technology [17].. The parametric ESR model is an appropriate model to reduce the selection bias and assure consistent results by capturing both the observed and unobserved heterogeneity that influences the outcome variable as well as the adoption decision [14].

The impact of coffee technologies on annual coffee yield under the MNESR framework follows two stages. In the first stage, adoption of coffee technologies is estimated using a multinomial logit model as selection as seen above, while in the second stage linear regressions after testing the assumption of classical linear regression were employed to assess the association between an outcome variable and adoption of coffee technologies (Bekele Shiferaw et al., 2014).

Farmers may endogenously self-select adoption or non-adoption, so decisions are likely to be influenced systematically both by observed and unobservable characteristics that may be correlated with the outcomes of interest. To disentangle the pure effects of adoption, model the farmers' choice of combinations of coffee technologies and the impacts of adoption in the coffee annual yield framework, a relatively new selection-bias correction methodology based on the multinomial logit selection model. This approach allows us to get both consistent and efficient estimates of the selection process and a reasonable correction for the outcome equations [3]. This framework has the advantage of evaluating both individual and combined practices, while capturing the interactions between the choices of alternative practices.

Consistent estimates of the yield functions specified below are important to unravel the pure effect of coffee technologies on annual coffee yield. The relationship between coffee yield (Qji) and a set of exogenous variables Z (institutional access, demographic factors, resources, etc.,) is estimated for each chosen combination of coffee technologies following the [2] flexible moment-based approach and the [2]. multinomial selection-bias correction framework. The base category, non-adoption of coffee technologies (i.e., $V_0M_0$), is denoted as j = 1. In the remaining combinations (j = 2, 3, 4), at least one coffee technologies are adopted. The stochastic production function to evaluate the annual yield implications of coffee technologies adoption for each regime (coffee technologies combination) j is given as:

$$\begin{cases} \text{Regime 1: } Q_{1i} = \alpha Z_{1i} + \theta Z_{1i} + U_{1i} \\ \qquad \vdots \\ \text{Regime J: } Q_{Ji} = \alpha Z_{Ji} + \theta Z_{Ji} + U_{Ji} \end{cases} \quad (4)$$

where Q is the coffee yield per hectare of the ith farmer on a plot in regime j, Z is as defined above, and u denotes error terms that capture the uncertainty faced by farmers and satisfies E(u) = 0. In order to get consistent estimates, equation (2) is augmented by including the mean of plot varying covariates, average plot size to control for the unobserved heterogeneity, including the level of inputs, can help to address plot-specific unobservable as they contain useful missing information regarding land quality. If farmers accessed private information about unobservable effects such as how good the soil is on the plot, they will accordingly adjust their factor input decisions [10].

If the u's and ε's are not independent, a consistent estimation of a h requires the inclusion of the selection correction terms of the alternative choices in (1). [3] show that consistent estimates of a and h in the outcome equations (1) can be obtained by estimating the following MNESR models:

$$\begin{cases} \text{Regime 1: } Q_{1i} = \alpha Z_{1i} + \sigma_1 \hat{\lambda}_{1i} + \theta \bar{Z}_{1i} + U_{1i} \;\; I = 1 \\ \qquad \vdots \\ \text{Regime J: } Q_{Ji} = \alpha Z_{Ji} + J \hat{\lambda}_{Ji} + \theta \bar{Z}_{Ji} + U_{Ji} \;\; I = j \end{cases} \quad (5)$$

Here, e is the error term with an expected value of zero, r is the covariance between ε and u, k is the inverse Mills ratio computed from the estimated probabilities in equation (3) as follows:

$$\lambda_{ji} = \sum_{m \neq j}^{J} p_j \left[ \frac{\hat{p}_{mi} \ln(\hat{p}_{mi})}{1-\hat{p}_{mi}} + \ln(\hat{p}_{ji}) \right]; p \quad (6)$$

$p$ is the correlation coefficients between ε and u. In the multinomial choice setting, there are J - 1 selection correction terms to be included in the production one for each combination of coffee technologies.

As shown by [2] the error terms in equations (5) and (6) are likely to exhibit heteroscedasticity. To deal with heteroscedastic problems, standard errors in equations (5) and (6) are bootstrapped. For equations (5) and (6) to be identified, it is important to use a selection instrument in addition to those automatically generated by the non-linearity of the selection model of adoption. Getting a true instrumental variable is a challenge (if not impossible) in many empirical analyses. In equation (5), we excluded the following set of instruments from the coffee yield function results using a simple falsification test [6] confirm that, in nearly all cases, these variables are jointly significant in the adoption.

# 3. Estimation of the Counterfactual and Treatment Effect

Following [14, 19], the impact literature, we describe how the multinomial endogenous switching treatment regression model can be used to compute the counterfactual and average adoption effects. The counterfactual is defined as the crop yield and downside risk of adopters which would have obtained if the returns (coefficients) on their characteristics had been the same as the returns (coefficients) on the characteristics of the non-adopters, and vice versa. In addition to addressing selection bias due to unobserved heterogeneity, this approach also controls for selection bias due to observed heterogeneity. From equation (4), the following conditional expectations for each outcome variable can be computed:

Adopters with adoption (actual)

$$E[Q_{ji} | I = j, Z_{ji}, \bar{Z}_{ji}, \hat{\lambda}_{ji}] = \alpha_{ji} Z_{ji} + \theta_j \bar{Z}_{ji} + \sigma_j \hat{\lambda}_{ji} \quad (7)$$

Non adopters with non-adoption (actual)

$$E[Q_{1i} | I = 1, Z_{1i}, \bar{Z}_{1i}, \hat{\lambda}_{1i}] = \alpha_{1i} Z_{1i} + \theta_1 \bar{Z}_{1i} + \sigma_{1\varepsilon} \hat{\lambda}_{1i} \quad (8)$$

Adopters had decided to non to adopt (counterfactual)

$$E[Q_{1i} | I = j, Z_{ji}, \bar{Z}_{ji}, \hat{\lambda}_{ji}] = \alpha_1 Z_{ji} + \theta_1 \bar{Z}_{ji} + \sigma_{1\varepsilon} \hat{\lambda}_{ji} \quad (9)$$

Non adopters had decided to adopt (counterfactual)

$$\mathrm{E}\left[Q_{1i}|I = 1, Z_{1i,}\bar{Z}_{1i}, \hat{\lambda}_{1i}\right] = \alpha_j Z_{1i} + \theta_j \bar{Z}_{ji} + \sigma_{j\varepsilon}\hat{\lambda}_{1i} \quad (10)$$

Equations (7) and (8) represent the actual expected maize yield (or mean yield functions) actually observed in the sample for adopters and non-adopters, respectively, while equations (9) and (10) are their respective counterfactual expected maize yields. The use of these conditional expectations allows us to calculate the average adoption effects (average impact on yield) on adopters (ATT).8 The ATT is defined as the difference between equations (8) and (9)

$$ATT = \mathrm{E}\left[Q_{ji}|I = j, Z_{ji,}\bar{Z}_{ji}, \hat{\lambda}_{ji}\right] - \mathrm{E}\left[Q_{1i}|I = 1, Z_{1i,}\bar{Z}_{1i}, \hat{\lambda}_{1i}\right]$$
$$= Z_{ji}\left(\alpha_j - \alpha_1\right) + \bar{Z}_{ji}\left(\theta_j - \theta_1\right) + \hat{\lambda}_{ji}(\sigma_i - \sigma_1) \quad (11)$$

Counterfactual difference is the ATU of the coffee technologies.

$$ATU = \mathrm{E}\left[Q_{1i}|I = j, Z_{ji,}\bar{Z}_{ji}, \hat{\lambda}_{ji}\right] - \mathrm{E}\left[Q_{1i}|I = 1, Z_{1i,}\bar{Z}_{1i}, \hat{\lambda}_{1i}\right]$$
$$= Z_{ji}\left(\alpha_j - \alpha_1\right) + \bar{Z}_{ji}\left(\theta_j - \theta_1\right) + \hat{\lambda}_{ji}(\sigma_i - \sigma_1) \quad (12)$$

# 4. Impact of Coffee Technologies on Coffee Yield

The objective of this study was to analyze the impact of adopting coffee technologies on annual yield of coffee status. The multinomial endogenous switching regression (MNESR) model was employed to answer this objective. In the first regime of the multinomial endogenous switching regression model, the researcher estimated the determinants of the adoption decision of households as discussed in Section 4.4. above the second stage of the MNESR model was used to estimates the effect of different variables on annual coffee yield for both adopters and non-adopters of coffee technologies. The selection equation after the participation equation includes all the variables in the participation equation and instrumental variables to improve identification. The instrumental variables used in the model were an average plot to home distance and walking distance to farmers training center for different category based on their significance for the dependent variable and the outcome variable. Based on the falsification test these variables were found to affect the adoption of coffee technologies significantly but have no direct effect on annual household income, suggesting that the variables meet the criteria to be instrumental variables were walking distance to farmers plot and walking distance to FTC the falsification test result is shown in the appendix as shown in there the falsification test approve those variables are an instrumental variable. From the MNESR model result, as seen in the appendix table different factors affecting the annul coffee yield for both adopters and non-adopters of coffee technologies. The model result is indicated in the table in the appendix.

The impact of coffee technologies adoption on annual yield is shown in Table 1 it is the value after comparing expected coffee yield (kg/hectare) under the actual case that the farm household adopted a particular combination of coffee technologies, and the counterfactual case that they did not; that is, the researcher compare columns (A) and (B) of Table 1. Column (C) presents the impact of each coffee technologies combination on annul coffee yield, which is the adoption effect (ATT), calculated as the difference between columns (A) and (B). Controlling for the effects of several covariates and the selection bias stemming both from unobserved and observed factors on mean yield, the adoption of coffee technologies is associated with significant coffee yield improvements. The highest yield effect, which is 5833.62kg/ha of red cheery coffee or 972.27 kg/ha of clean coffee because the ration of clean coffee to red cherry coffee is 1:6, is obtained from the joint adoption of coffee technologies (V1S1) which is greater than non-adopter by 391.81kg/ha of clean coffee, which is also greater than the effect of each practice independently, suggesting complementarity in benefits.

Before running a multiple linear model for the outcome variable, the tests for the assumption of classical liner model were tested using an appropriate method and the result of the test is shown in the append of the paper.

***Table 1.*** *Average expected coffee yield with adoption of coffee technology effects.*

| | **Treatment effect** | **Decision stage** | | |
|---|---|---|---|---|
| | | **To adopting (j = 2, 3, 4)** | **Not to adopting (j = 1)** | **Adoption Effects** |
| | ATT | 5220.68 | 3047.04 | 2173.63*** |
| $E(R_{ij}\|I = 2) - E(R_{1j}\|I = 2)$ | ATU | 5301.46 | 3252.96 | 2048.49*** |
| | HE | 80.78 | 205.92 | 125.14*** |
| | ATT | 4025.50 | 3230.75 | 794.75*** |
| $E(R_{ij}\|I = 3) - E(R_{1j}\|I = 3)$ | ATU | 3703.78 | 3252.96 | 450.81*** |
| | HE | 321.72 | -22.21 | 343.94*** |
| | ATT | 5833.62 | 3482.71 | 2350.90*** |
| $E(R_{ij}\|I = 4) - E(R_{1j}\|I = 4)$ | ATU | 5353.68 | 3252.96 | 2100.71*** |
| | HE | 479.94 | 229.75 | 250.19*** |

***,1% level of significance; ATT=Average treatment effect on treated; ATU=Average treatment effect on untreated Note: (I) = (a)-(c) (II) = (d)-(b) (III) = (e)-(f) HE =ATT-ATU

Source: Own survey result (2022)

## 5. Conclusion

This study was conducted on impact of annual coffee yield in Jima zone south western Ethiopia. Jima zone naturally endowed with a favorable agro ecology that encourage farmers to produce coffee. Objective of the study were to asses the impact of those coffee technologies in coffee annual yield. The multinomial endogenous switching regression model showed that in terms of annual coffee per yield adopters of both technologies were increased by 3482.71. kg/ha red cherry coffee or 580.45kg/ha of clean coffee form non adopter of an improved coffee variety and proper management or slashing 3 times a year. Non adopter of an improved coffee variety and proper management adopter 764.75kg/ha of red cherry coffee or 127.45kg/ha of coffee is obtained. For an adopter of an improved coffee variety and non-adopter of proper management additional 2173.63kg/ha of coffee is obtained than the base category or non-adopter of both technologies. Based on this, we can conclude that coffee technologies adoption contributes to improving annual yield of coffee.

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