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Multidimensional Poverty Dynamics in the Context of Climate-induced Shocks in Ethiopia

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Abstract

This paper examines the effect of climate-induced shocks on multidimensional poverty indicators in Ethiopia using data from the Ethiopian Socioeconomic Survey (ESS) collected under the Living Standard Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) of the World Bank. The empirical strategy used for the study is a dynamic mixed probit regression model that helps to account for unobserved heterogeneity and initial condition problem by assuming state dependence of multidimensional poverty over time. The study revealed that the standard of living dimension is the most significant contributor to multidimensional poverty for rural and small towns. Drought shocks and high rainfall has an adverse effect on multidimensional poverty. In addition, factors that contribute to multidimensional poverty include the age of households, family size having more adult equivalents, better farm assets, more income from PSNP, access to extension and credit, households living in rural areas, and Afar region and Dire Dawa city administration and have a low chance of exiting from poverty. However, households with a higher dependency ratio, who are better educated, have more noncultivated land, and live in the Somali and Harari regions are less exposed to multidimensional poverty and have a high chance of exiting from multidimensional poverty. To attain the poverty reduction target of sustainable development goals, federal and regional governments should allocate resources for the improvement of the living standard dimensions of social welfare. To improve multidimensional poverty in all its form, a one-size-fits-all policy may not produce notable outcomes. Therefore, policymakers should target households experiencing a multidimensional poverty trap to fight poverty and give priority to attributes such as climate-induced shocks, regional variations, and household characteristics.

Keywords: Multidimensional poverty, dynamic mixed effect probit model, unobserved **heterogeneity, entry and exit probabilities, Ethiopia.**

JEL Classification: O12, Q12

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1. Introduction

Achieving sustainable and inclusive economic growth has gained much attention worldwide. Eradication of all forms of poverty has been a key among the Sustainable Development Goals (SDGs). Among those agendas are to improve multidimensional well-being indicators (Heshmati and Kim, 2014; Heshmati *et al*., 2015; Ravallion, 2017; Heshmati, 2018; Kim, 2019; Mekonnen and Almas, 2021). The 2015 SDGs call to "end poverty in all its forms everywhere" by 2030 is one of the sustainable main goals (UNDP, 2015 and UNDP, 2018). Multidimensional poverty in Ethiopia is a significant development problem and a source of socioeconomic chaos that threatens the survival and stability of the society. As a result, poverty reduction is the country's top development agenda, requiring an inclusive approach to design anti-poverty policies, strategies, and programs. Accordingly, the Ethiopian government has been designing and implementing various transformation plans to reduce poverty and improve the living standards of the people, which brings about sustainable national development. The major transformations plans implemented include the Plan for Accelerated and Sustainable Development to End Poverty (PASDEP) and a fully integrated Growth Transformation Plans (GTP I and II) to eradicate poverty through the development of a Climate-Resilient Green Economy (CRGE) (MoFED, 2016).

Over the last two decades, the Ethiopian economy grew at 10.7 percent on average (World Bank, 2015), and multidimensional poverty decreased substantially, albeit from a relatively high baseline, between 2002 and 2009 (Mwanakatwe and Barrow, 2010). Several studies have indicated that multidimensional poverty in Ethiopia remains high (UNDP, 2015; Alkire and Kanagaratnam, 2018). The country is seconds next Niger in multidimensional poor people in Africa (Apablaza and Yalonetzky, 2013; OPHI 2018). Among the multidimensional poverty dimensions, living standards contribute the most to the poverty dimension, followed by education, with the most negligible contribution to the health dimension (Tigre, 2018:2020). Furthermore, climate-induced and extreme weather shocks exacerbate the wellbeing of households in developing countries and specifically in Ethiopia (Twongyirwe *et al*., 2019; Halkos and Skouloudis, 2020; Lottering *et al*., 2020; Titay *et al*., 2021).
In 2019, the multidimensional poverty index leftovers at 83.5 percent, with an intensity of deprivation of 58.5 percent (Human Development Report, 2020). According to the Oxford Poverty and Human Development Initiative (OPHI) (2014) and OPHI (2018), in 2011, based on the Multidimensional Poverty Index (MPI), 87 percent of Ethiopia's population was poor. This means being deprived of at least one-

third of the weighted MPI indicators. Other studies that explored the multidimensional aspect of poverty in Ethiopia found that the reduction in poverty measured by the MPI declined by only approximately 10 percent compared to the 33 percent decrease in monetary poverty during the same period (Hill *et al*.,2017; Ogutu and Qaim, 2019). Overall, with over 85 percent of the population deprived, the index suggests that the country's poverty is deep-rooted and complex (Alemayehu *et al*., 2015). Severe multidimensional poverty is more prevalent in rural households than in urban households. In Ethiopia, most households considered multidimensional poor might also be considered severely poor (Dotter *et al*., 2017). Eradication of poverty if possible or reducing poverty in all forms is an essential priority, although it is challenging for most developing countries (Dercon and Porter, 2014).

Previous studies on multidimensional poverty focus on cross-sectional data and specific locations, and most research papers focused on descriptive statistical results, neglecting the dynamics over time (Alazzawi and Said, 2013; Mekonnen, 2015; Roelen, 2017; Degye, 2020; Misganaw *et al*., 2020; Bantayehu and; Singi, 2021; Desawi *et al*., 2021; Galgalo *et al.*, 2021; Mekonnen and Almas, 2021; Tsegaye, 2021). Studies that estimated multidimensional poverty using panel data estimation (Mekonnen, 2015; Seff and Jolliffe, 2017; Williams and Moral-benito 2017; Tigre, 2018; Kim, 2019; Migbaru and Zerayehu, 2020; Tigre, 2020) missed the triggers of multidimensional poverty over time. Specifically, none of them tried to see the systematic connection between climate-induced shocks and multidimensional poverty from the Ethiopian perspective. However, climate-induced shocks affect people's behavior toward climate change adaptation and coping strategies and consequently threaten the goal of eradicating extreme poverty by 2030. Thus, it becomes a reality to examine and quantify the effect of climate-induced shocks on multidimensional poverty dynamics in Ethiopia is important to provide context-specific information for policymakers to minimize the effect of climate-induced shocks and thereby improve the wellbeing of the people.

2. Methodology

2.1 Data

The study employed nationally representative panel data from the Ethiopian Socioeconomic Survey (ESS) collected through the Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) collected by the World Bank in collaboration with the Central Statistical Agency (CSA) of Ethiopia. The ESS sample is designed to represent rural and small-town areas of Ethiopia. The ESS

sample size provides estimates at the national level for rural and small-town households in nine regions, including Amhara, Oromia, SNNP, Tigray, Afar, Benishangul Gumuz, Gambella, Harari, and Somali regional state and Dire Dawa city administration of Ethiopia. The data were collected in three rounds (2011/2012, 2013/2014, and 2015/2016) conducted every two years. Rainfall data were obtained from Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) (Peterson *et al*., 2013) using satellite imagery and station data to create a grid of rainfall time series with a resolution of 0.05^0. Finally, this study has considered a balanced sample of 3220 households in each round with the corresponding sample weight for the poststratification adjustments to ensure that all regions are to be represented.

2.2 Conceptual Framework

Poverty is a social phenomenon that goes beyond the economic sphere. One way of defining poverty is by letting the poor explain their thought about poverty. For instance, Foster *et al*. (2013) defined poverty as the absence of acceptable choices across crucial life decisions. One pair of approaches comprises the 'welfarist' and the 'nonwelfarist' approaches. Economists, however, often prefer to view the concept of wellbeing in terms of the 'welfarist' approach by taking expenditure on goods and services consumed by households valued at market prices to categorize a person as poor or nonpoor. Unlike the monetary approach, the capability approach provides good ground to measure poverty from a multidimensional perspective. Sen (1990) defines poverty as a lack of capabilities to manage one's life and capabilities to function. The capability set of households/individuals depends on many covariates, including private and public resources and the general environmental context. The achievement of different services and utilities depends on personal resources and the government's availability and accessibility of public goods freely/subsidized (Sen, 2009).

The capability approach emphasizes the outcome characterization of an individual's quality of life that implies a shift from monetary indicators to nonmonetary indicators for evaluating well-being; this allows us to capture the notion of poverty that people experience in everyday life (Sen, 2009). Thus, one can analyze the poor, rich, basic, and complex capability using this approach (Aliker, 2007). However, one of the controversial questions is what constitutes the basic list of capabilities. Sen responds to such questions in their use, and the weight given priorities vary across societies. It is not easy to give a specific list of capabilities

(2009). The definition of capability does not define a certain subset of capabilities as peculiar importance; rather, the selection of capabilities to focus on is value judgment (Aliker, 2005).

The shock wave report (Hallegatte *et al*., 2016) and a companion paper (Hallegatte and Rozenberg, 2017) confirmed that climate shocks could adversely affect poverty, even factoring in future reductions in vulnerability. Most effects of climate change on poverty could be avoided if appropriate policies were formulated at a national level and minimized if households have developed resilience capacity. However, in a pessimistic scenario where infrastructure investments are biased against poor people and social protection and health coverage remain limited, climate shocks could move people into poverty (Hallegatte *et al.,* 2018). Wunder *et al*. (2018) found that rural households in developing countries depend on livelihood sources. The size and composition of these livelihood contributions are sensitive to climate-induced shock. According to Narloch and Bangalore (2018), the relationship between poverty and environmental risk varies as a function of the channels through which poverty and risk interact, using a set of consistent data and methods while holding a constant national context. At the household level, poorer households face higher environmental risks than their counterpart.

Extreme weather events are fundamental in estimating the effect of climate variability and extreme events. According to Hallegatte *et al.* (2017), poverty increases after climate shocks, widespread floods, and drought. Winsemius *et al*. (2018) find that poor people are often disproportionally exposed to droughts and floods, mainly if their livelihood is dependent on rain-fed agriculture. Poor people are more exposed to high temperatures than the average. Because poor people are more likely to work as outdoor workers exposed to weather shocks. The results suggest an enormous vulnerability of poor people to heat extremes and potentially significant distributional and poverty implications of climate change (Park *et al*., 2018).

The increase in the frequency and intensity of extreme events expected from climate change (IPCC, 2014) implies that climate change will represent a growing obstacle to poverty reduction unless resilience is dramatically improved. Rainfall increases above the optimal level, and high temperature is positively associated with poverty (source?). However, if the absorptive capacity and copying strategies increase, the adverse effect of climate-induced shocks on poverty (Gao and Mills, 2018) can be minimized. Moreover, multidimensional poverty has a dynamic nature that would possibly result from the interaction of household demography, capital (human, social, and resources), economic activities, household shocks, and

geographic locations (Mulugeta *et al*., 2017; Fantay *et al.,* 2019) in addition to climate-related variables.

Therefore, this study adopted and used the integrated theoretical approach of capability theory and multidimensional poverty theory. Analytical frameworks of the effect of climate-induced shocks are uncertain (Rahm and Huffman, 1984). Thus, the occurrence of shocks can be modeled as climate-induced shocks and multidimensional poverty in a random utility framework following the literature (Becerril and Abdulai, 2010; Di Falco *et al.,* 2011; Kassie *et al.,* 2011; Shiferaw *et al.,* 2014; Khonje *et al.,* 2015). Therefore, it is assumed that households that have coping strategies and absorb shocks will face fewer shocks. However, absorptive capacity also depends on the endowments of resources of the household.

2.3 Measurement of Variables

Climate-induced shocks are measured in dummy and continuous variables that measured the climate-induced shocks. Following Ward and Shively (2015) and Michler *et al.* (2019), estimated rainfall was taken as a shock as normalized deviations in single annual and seasonal rainfall from the expected yearly and seasonal historical rainfall. Then, the rainfall is normalized using the historical mean and standard deviation. A shortage of rainfall is identified as one standard deviation away from the historical and seasonal mean rainfall and was then coded as a binary dummy variable (=1 if the household experienced a shortage of rainfall at time t and 0 otherwise). The estimation of poverty using the counting method defines the various dimensions and indicators of household wellbeing. Based on Alkire (2011) and Alkire and Santos (2014), this research has taken three core dimensions and ten indicators. The dimensions and indicators and corresponding weights were used in multidimensional poverty analysis and are listed in Appendix Table 1.

Aggregation of multidimensional poverty index of the total households (n_t) in each wave representing the population of interest and c_t indicators for selected dimensions at t period t for which $c_t \geq 2$ after the data are available and the range of dimensions and indicators have been selected, researchers have achieved the level matrix $n_t \, x \, c_t$ households and c_t-indicators of the selected dimensions. Let $\sum Y_t = \left[Y_{ijt}\right]$ denote the $n_t \, x \, c_t$ matrix of achievement for household i across indicator j at a time. Finally, a deprivation score matrix of $n_t \, x \, c_t$ dimensions with values 0 and 1. Alkire and Foster (2011), Alkire and Santos (2014), and Alkire and Jahan (2018) define the severely poor (raising the second cutoff), making it harder

to fall into severe poverty as several original multidimensional poverty indices. Accordingly, a household is identified as poor if it has a deprivation score greater than or equal to 1/3 (33%) (Alkire and Santos, 2011; OPHI, 2014; OPHI, 22017; Dotter and Kalsen, 2017; Alkire and Jahan, 2018) for the respected year.

2.4 Estimation Technique

Climate-induced shocks (Hallegatte *et al*., 2016) and a companion paper (Hallegatte and Rozenberg, 2017) confirmed that climate shocks could significantly impact poverty headcount, even factoring in future reduction vulnerability. Most effects of climate change on poverty could be avoided if good policies were developed. However, in a pessimistic scenario where infrastructure investments are biased against poor people and social protection and health coverage remain limited, climate change could move people into poverty (Hallegatte *et al.,* 2018).

State dependence of multidimensional poverty over time and the amount of inertia in the previous multidimensional poverty status is essential for fighting poverty in Ethiopia. However, to examine the true state dependence, only taking the one-time lag multidimensional poverty is impossible (Heckman, 1981; Grotti and Cutuli, 2018). Therefore, using a dynamic random effects probit model with an unobserved heterogeneity estimation technique helps solve the state dependence and initial condition problems.

The dynamic mixed-effects probit model has increasingly been applied in social research to analyze the effect of covariates and dynamics of persistence in dichotomous outcomes. The dynamic binary mixed-effects model is well suited to tackle the true state dependence of multidimensional poverty at the household level. The effect of lagged multidimensional poverty on current multidimensional poverty is accounted for as unobserved heterogeneity (Devicienti and Poggi, 2007). Heckman (1981) suggested that dynamic binary panels discriminate between spurious state dependence and true state dependence. A spurious state of multidimensional poverty increases the probability of ascending to multidimensional poverty.

Therefore, to incorporate both state dependence and unobserved heterogeneity, the dynamic random effects probit model was developed by Grotti and Cutuli (2018). It implements Wooldridge's (2005) simple solution to the initial condition problem in the alternative proposed by Rabe-Hesketh and Skrondal (2013). The dynamic mixed effect model provides estimates of transition rates and a set of

associated statistics. It depends not only on the lag value of the outcome variable but also on other variables (unobserved heterogeneities) to account for state dependence.

To overcome the initial condition problem, which refers to the beginning of a stochastic process leading to the experience of the outcome may not correspond to the initial value of the outcome variable that the researcher observes. This model used conditioning on the response at the initial period, which was proposed by Wooldridge (2005) and Grotti and Cutuli (2018). Considering state dependence by considering the amount of inertia in the previous status of multidimensional poverty is essential for fighting poverty in Ethiopia. However, it is impossible to identify the true state dependence only by taking the one-time lag multidimensional poverty (Heckman, 1981; Grotti and Cutuli, 2018). Therefore, using a dynamic random effects probit model with an unobserved heterogeneity estimation technique helps solve the state dependence problem and the initial condition problem.

$$Y_{it}^{*} = X_{it}\beta + \gamma Y_{it-1} + C_i + \lambda R_{it} + Y_{it-1} + \varepsilon_{it} \qquad \textbf{(1)}$$

Y_{it}^{*} is an unobserved latent variable, and it is a dummy indicator Y_{it}=1 if household i is below the multidimensional poverty line for unit *i (i = 1, 2,……. N*), at time *t,* and zero otherwise.

X_{it} is a vector of time-variant and time-invariant covariates, assumed to be strictly exogenous, conditional on the unit-specific unobserved effect C_i. The lag of the latent outcome variable Y_{it-1} captures the state dependence, and ε_{it} is for error terms. λR_{it} is a vector of time-varying climate-induced shocks of household *i* in year t. β is the corresponding vector of parameters estimated. The unit-specific unobserved effect can be written as:

$$C_1 = \beta_0 + Y_{i0}\beta_1 + Z_i^{*}\beta_2 + Z_{i0}\beta_3 + \beta_i \qquad \textbf{(2)}$$

Here, Y_{i0} and Z_{i0} represent the initial values of the response variable and the time-varying and time-varying explanatory variables with climate-related shocks. $Z_i^{*} = \frac{1}{T}\sum_{i=0}^{T} Z_{it}$ stands for the within-unit averages of the covariate variables, where the averages are based on all periods t=0,1,2,….T. Finally, β_i is the unit-specific time-constant error term, which is assumed to be normally distributed with mean 0 and variance σ_{β}^{2}. Additionally, the expected (average) spell duration and the steady-state (long-run) probability were computed.

The probability to entry and persistence are computed using the postestimation commands, and then the probability to exit, expected spell duration, and steady-state probability are estimated indirectly as:

$$P(0|1) = 1 - P(1|1) \quad \textbf{(3)}$$

$$Expected\ (average) duration\ exit\ from\ multidimentional\ poverty = \frac{1}{P(0|1)} \quad \textbf{(4)}$$

$$Expected\ (average) duration\ entry\ from\ multidimentional\ poverty = \frac{1}{P(1|1)} \quad \textbf{(5)}$$

where $P(0|1)$ is the probability of exit from multidimensional poverty at time t conditional on being multidimensional poor at time $t-1$, $P(1|1)$ stands for the probability of entry into multidimensional poverty at time t conditional on being nonpoor at $t-1$ and $P(1|1)$ the probability of persistence in multidimensional poverty.

3. Results and Discussion

3.1 Descriptive Statistics

The deprivation of households in each dimension and indicator by survey year is presented in Table 1. The cooking fuel, improved sanitation, access to electricity, and school attendance had a higher percentage of deprivation up to grade eight. For instance, approximately 86, 97, and 98 percent of the rural and small-town households in 2012, 2014, and 2016, respectively, do not have electricity, improved sanitation, and access to clean cooking energy. This result is also strongly affirmed by the World Bank (2018), which shows that more than 57 percent of the population in Ethiopia was deprived of electricity[5], and approximately 95 percent of the population does not have access to clean energy for cooking.

[5] The result of electricity deprivation is high as compared with World Bank (2018). This study only considered rural and small-town areas, whereas the World Bank includes Ethiopian urban areas.

Table 1: Household deprivation by different indicators in percentage

Dimensions	Indicators	Deprivation by wave			
		2012	2014	2016	Pooled
Education	Years of schooling	37.2	33.5	30.4	33.4
	School attendance	59.1	57.9	57.6	58.1
Health	Child mortality	9.9	11.6	34.6	19.9
	Nutrition	25.1	2.3	2.3	8.8
Living standard	Access to electricity	88.8	85.4	83.2	85.6
	Improved sanitation	95.7	94.8	99.8	96.9
	Improved drinking water	10.2	7.4	5.5	7.5
	Housing quality	2.8	3.3	4.7	3.7
	Cooking fuel	97.2	98.5	97.9	97.9
	Assets ownership	45.0	56.7	53.1	52.0

***Observations are weighted under survey design to make results representative of all individuals in Ethiopia. The balanced panel sample size was 3,220 households in three waves. Standard errors are adjusted for stratification and clustering.
Source: Authors' computation based on ESS (2012, 2014, and 2016)

The dimensional health indicators (child mortality and nutrition) were less deprived than the rest of the indicators. The Ethiopian government successfully decreases child mortality and child nutrition and implies that the government pays great attention to health services. UNDP (2015), Migbaru and Zerayehu (2020), and Migbaru (2021) also reported that the deprivation in mortality and malnutrition were lower in Ethiopia and declined over time. In some indicators, the percentage of deprivation for the three rounds of years shows an inconsistent path, although in most indicators, the percentage of deprivation decreases from wave to wave. However, the source of electricity shows minimal improvement over time but is almost effectively stagnant and nonexistent, with a prevalence of this deprivation of more than 83 percent in the three waves. According to the World Bank (2018) and Megbaru and Zerayehu (2020), households are deprived of access to clean energy for cooking, access to electricity, and improved sanitation. Additionally, household houses are made of mud and unfinished floors. Therefore, the government needs to pay more effort to the sources of energy for cooking fuel, improved sanitation, and access to electricity to improve the living standards of households.

3.2 Multidimensional Poverty Dynamics

The results of the dynamic random effect probit model are shown in Table 2. Below presents the state of dependence and effect of unobserved heterogeneity, including climate-induced related shocks, socioeconomic factors, and institutional actors. The likelihood ratio statistics (p=0.000) and Wald statistic (chi^2 (93) = 1214.91) are used to test the state dependence of the multidimensional poverty status with a lag of multidimensional poverty and other covariates in the model. The result indicates that time-variant and invariant covariates simultaneously affected multidimensional poverty status. Furthermore, one percent of the significance of one-time lag multidimensional poverty (1 L. M_poverty) ensured that the dynamic random effect probit model has good explanatory power.

The lagged value of multidimensional poverty (L.M_poverty) that captures genuine state dependence has a positive and significant coefficient. This suggests the presence of dynamics of the state of dependence. This implies that the current multidimensional poverty status of the household is affected by the previous period's multidimensional poverty status. In other words, households that were multidimensional poor in the preceding period were more likely to experience multidimensional poverty in the next period and augment the multidimensional poverty loop than those who were not multidimensional poor. Singu (2016) and Stromquist (2019) also confirm deprivation in the education dimension.

Unexpectedly, most climate variability and climate-induced shocks are not statistically significant except for self-reported drought and mean precipitation/rainfall. As expected, households that reported the experience of drought shocks were more likely to be poor. At the household level, the pathways of climate-induced shocks occur through crop production and the rearing of livestock.

The livelihood depends on agriculture or shocks directly affecting different endowments and capitals. Additionally, households that obtain higher average rainfall are exposed to an experience of multidimensional poverty. High rainfall could cause flooding and, as a result, affect the house, water, and waterborne diseases. This result is consistent with the findings of Tasew (2011), Tassew and Adam (2012), Tasew and Adam (2013), and Kedir *et al*. (2017), who argue that drought-related shocks deplete different essential endowments and the productive capacity of households. Drought is the main causal factor triggering poverty through changing livelihoods (Yue *et al*., 2013). Moreover, households across the tropics already face numerous risks, including pest and disease outbreaks, extreme weather events, and market shocks that directly affect health, education, and living standards (Celia *et al*., 2014).

Table 2: Regression results of the dynamic mixed-effects probit model

Variables	Coefficient	Robust std. error
1 L.M_poverty	0.4560***	0.0521
1.M_poverty__0	0.2121***	0.0556
Production shock	0.0473	0.1038
Market shock	0.0243	0.0527
Drought	0.2484**	0.1238
Annual rainfall shortage	-0.1175	0.0805
Growing season rainfall shortage	0.1297	0.0845
Temperature	0.0074	0.0071
Precipitation/rainfall	0.0002***	0.0001
Annual rainfall variability	-0.0001	0.0005
Sex (male=1)	-0.1390	0.1750
Age	0.0126**	0.0054
Adult equivalent	0.3150***	0.0365
Dependency ratio	-0.0523**	0.0224
Education	-0.0082***	0.0029
Cultivated land	0.0132*	0.0080
Not cultivated land	-0.0150**	0.0070
Farm asset index	0.3766***	0.1058
PSNP income	0.0003**	0.0001
Distance to market	0.0002	0.0004
Access to extension	0.1384***	0.0431
Access to credit	0.2061**	0.0825
Residence(rural=1)	0.2036***	0.0674
Afar	0.2349*	0.1218
Amhara	-0.0736	0.0790
Oromia	0.0254	0.0845
Somalie	-0.1846*	0.1050
Benishangul Gumuz	0.1551	0.1270
SNNP	0.0006	0.0878
Gambelia	-0.0671	0.1276
Harari	-0.2707**	0.1185
Dire Dawa	0.2838**	0.1204
Dependency ratio_0	0.1314**	0.0456
Education_0	-0.0073**	0.0036
Cultivated land__0	0.0134**	0.0061
Farm asset index__0	0.1599***	0.0615
m__Age	-0.0207**	0.0092
m__Cultivated land	-0.0129**	0.0053
m__Farm asset index	-0.5507***	0.1709
Constant	-1.0709***	0.2351

Symbols: ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively
Source: Authors' computation based on ESS, 2012, 2014, and 2016.

The estimation result also revealed a statistically significant and positive effect of the initial condition of multidimensional poverty (M_Poverty_0). This implies that the initial condition of multidimensional poverty is associated with multidimensional poverty. The initial condition of the dependency ratio (dependency ratio_0), cultivated land (cultivated land_0), and farm asset index (farm asset index_0) had a positive effect and was statistically significant with unobserved factors. The initial condition of education (education_0) has been negatively associated with unobserved factors. This confirms that different household characteristics positively and negatively correlated with unobserved factors. Moreover, multidimensional poverty had a negative and statistically significant effect with the unit average of age (m_Age), cultivated land (m_Cultivated land) and farm asset index (m_farm asset index) with unobserved factors. It infers that the age of households, cultivated land and farm asset index are unobserved initial condition variables and are correlated with multidimensional poverty.

The age of households had a positive and significant influence on multidimensional poverty status at a five percent significance level. This implies that the higher the age of a household is, the more likely the household is to experience poverty. Households usually like to invest in human capital at a young age as they have enough time to obtain returns, not in aged household heads. The basic facilities and services readily increase with productive age as new skills and knowledge are acquired through life and work experience and by investing in education. Furthermore, this might be because older households had less productivity than adult time, resources, and authority, which would allow them to increase poverty than more productive younger and experienced households. Furthermore, when the family size rises in households, the demand for different services increases, and households even want to have their own house and other facilities. However, the result is in contrast to the finding of Depoju (2018), Migbaru, and Zerayehu (2020), who find that an increase in the age of the household head reduces the household's likelihood of being multidimensional poor initially until a threshold and then increases. Multidimensional poverty has a direct relationship, and older households are more likely to be in multidimensional poverty than younger households.

Adult equivalents in households have a positive and significant relationship with multidimensional poverty at a one percent significance level. This indicates that households with more adult equivalents are more likely to be under multidimensional poverty. A possible explanation for this result is that there will be stiff competition for using governmental services (multidimensional indicators and dimensions). The demand for different services and utilities will increase, leading households to be

poor in multidimensional aspects. A similar result was also reported by Anyanwu (2014), Meyer and Nishimwe-niyimbanira (2016), Adepoju (2018), Bikorimana and Sun (2020), and Mekonnen and Almas (2021), who argued that as household size increases, the likelihood of descending in poverty increases in developing countries, especially if there is no efficient and effective utilization of resources and services.

Unexpectedly, the dependency ratio of households had a negative and statistically significant effect on multidimensional poverty at five percent. This implies that households with a higher dependency ratio are less likely to experience multidimensional poverty. The dependent families (children and the eldest) are less likely to be independent of having their house quality, more likely to have school attendance than productive labor out of the family members, and less likely to be deprived. As shown in Appendix table 4, the contribution of living standards and education dimensions had a high contribution to multidimensional poverty. Therefore, the probability of being deprived of living standards and education for dependable families will be less than independent family size for two reasons. First, in the estimation of multidimensional poverty, if the age of a family member is less than seven years, it is not considered whether to say deprived or not in school attendance, then the probability of being deprived is less than that of an independent family. Second, the probability of sharing in standard living dimensions (services and utilities) is high and has less compaction than adult dimensions, leading to a lower likelihood of experiencing multidimensional poverty.

As expected, the education level of the household head was negative and statistically significant at a one percent level in affecting multidimensional poverty. As people become more educated, they become more productive, and the probability and capability to access different social services and earn more income make them less likely to be multidimensional poor. Education is an essential indicator of human capital and increases information acquisition and abilities, thereby increasing their decision-making on quality wellbeing, implying that the likelihood of multidimensional poverty decreases with households. This result is similar to the research findings of Amao *et al*. (2017), Adepoju (2018), Migbaru, and Zerayehu (2020).

The households with better-cultivated land, farm assets, and income from PSNP increased the probability of experiencing multidimensional poverty, whereas noncultivated land has the probability of declining the experience of multidimensional poverty. This could be because for farmers who have better-cultivated land, farm assets cannot easily be converted into liquid assets compared with other assets and are socially unacceptable to sell those assets unless the farmers

face very devastating issues. Therefore, those issues are a means to obtain basic needs but not end output by itself. Income from PSNP sometimes creates dependency syndrome unless managed properly. According to the World Bank (2020), the Productive Safety Net Program (PSNP) uses a key driver of rural poverty reduction as long as it is implemented to target households with awareness creation. Noncultivated land had a negative association with multidimensional poverty. This implies that better noncultivated land would decrease the experience of multidimensional poverty by increasing the probability of constructing a quality house, improving sanitation, and improving water. Bikorimana and Sun (2020) found that off/nonfarm income and remittance had a negative contribution to poverty dynamics. Result Table 2 also reported that access to extension services and credit positively affected the probability of experiencing multidimensional poverty. Households that have access to extension services and financial credit have an increased probability of experiencing multidimensional poverty.

Households with formal financial credit services were more multidimensional poor than those who did not have formal financial credit services. Formal financial credit services resulting from income gains are a means of smoothing consumption for different services and facilities when households face different shocks. Consequently, if households would not be able to repay the credit, an increase in the deprivation of improving access to sanitation, malnutrition, improved drinking water, education, and energy will be required such that declining household demand for these basic goods and services. The result is similar to Adepoju (2018) and Migbaru and Zerayehu (2020).

Time-invariant variables such as residence and region have been reported to have a significant effect on the experience of multidimensional poverty. Households living in rural areas are more prone to experience multidimensional poverty than households living in small towns. It may include developing different programs, the spread of education, health and living standards, and the other provision of various services that are less common in rural areas. This study also showed that households living in rural area settings, particularly in a location, are more likely to be located in a poverty situation. After all, rural households are less likely to participate in off/nonincome activities, have less access to improved water, improved sanitation health services, infrastructure development, and low service standards. The disparities in welfare between rural and urban areas are well recognized throughout Ethiopia. This result is similar to the findings of Jansen *et al*. (2015), Biyase and Zwane (2017), Lekobane and Seleka (2017), Bikorimana and Sun (2020), Migbaru and Zerayehu (2020) and Mekonnen and Almas (2021).

In terms of region, households living in the Afar region and Dire Dawa city administration are more likely to experience multidimensional poverty than households living in the Tigray region. However, households living in the Somali and Harari regions are less likely to experience multidimensional poverty than households living in the Tigray region. As shown in Appendix Table 7, the contribution of living standards and educational dimensions highly fluctuated in the Tigray region even though multidimensional poverty was relatively high in the Somalie and Harari regional states over time. The findings of MoFED (2015), CSA (2017), OPHI (2018), Mekonnen and Almas (2021), and Migbaru (2021) confirmed that in most indicators of multidimensional poverty, particularly sanitation, sources of energy for cooking and floors made performs very low in the Afar region and good in Somali and Harari compared with the Tigray region. It is probably related to the allocation of resources, the difference in implementing different projects and programs, and the cascaded policies for the last couple of years by regional and federal governments in Ethiopia.

3.3 Entry to and Exit from Poverty

In addition to true state dependence and unobserved heterogeneity on multidimensional poverty, the dynamic mixed-effects probit with unobserved heterogeneity estimation technique also estimates the exit, entry, and persistence probability. The entry probability and steady-state probability at different levels of statistically significant climate-induced shocks and other time-variant and invariant variables (see appendix table 7). Appendix Table 7 shows the entry ($\boldsymbol{P}(\mathbf{1}|\mathbf{0})$ and persistence probability ($\boldsymbol{P}(\mathbf{1}|\mathbf{1})$ at different levels of drought, mean rainfall/precipitation, age, family size in adult equivalent, educational level, dependency ratio, cultivated land, noncultivated land, farm asset index, income from PSNP, access to extension contact, access to financial credit, residence and regions conditional on their previous year multidimensional poverty status.

The entry probability and probability of persistence for those facing drought shocks (drought shock = 1) are 0.704 and 0.822, respectively. It is, therefore, due to drought shocks, keeping other covariates constant, increasing the multidimensional poverty dynamics over time by a 0.704 (entry risk) probability level and increasing the persistent risk (poverty trap) (0.823). Rainfall/precipitation, keeping other things constant, satisfies poverty dynamics over time both by increasing the entry risk (0.64), increasing persistent probability (0.772), and reducing the exit chances (0.228). Reliably, the expected mean duration (4.38 years) of poverty spells and the

predicted steady-state probability of poverty are significantly higher among those who currently have lower mean rainfall/precipitation.

Age, adult equivalent, cultivated land, farm asset index, income from PSNP, access to extension services, and access to financial credit, keeping other things constant by increasing entry risk (0.369, 0.6469, 0.6408, 0.6542, 0.6697 and 0.6971, respectively) and increasing the persistence probability (0.7661, 0.788, 0.7724, 0.7725, 0.7791, 0.7791 and 0.8163, respectively). However, the dependency ratio, education and noncultivated land decrease entry probability (0.6422, 0.6421 and 0.64, respectively) and persistent probability (0.7724, 0.774 and 0.77, respectively). Reliably, the expected mean duration of the poverty spell and the predicted steady-state probability of poverty are significantly higher among those covariates that positively affect the experience of multidimensional poverty. This implies that households with higher age, large adult equivalent, and better income from PSNP are more likely to stay under poverty for a longer time. The probability of exiting from poverty is low compared with households with relatively younger ages, small adult equivalents, and less income from PSNP (for details, see Appendix Tables 7 and 8).

The entry probability for those who live in rural areas increased by 0.6489 compared with households who lived in small towns. The entry probabilities are high, and exit probabilities are lower among households living in rural areas than those living in small-town areas. Households living in rural areas are less likely to exit from multidimensional poverty than small towns. According to the World Bank (2018), most Ethiopian rural areas have improved sanitation, improved water sources, access to electricity, clean energy for cooking, and quality houses not built from wood and mud with unfinished floors. In addition, the entry probability of households living in Afar and Dire Dawa increases by 0.7151 and 0.7327, respectively, compared with the Tigray region. The households living in Somali and Harari, keeping other things constant, satisfy poverty dynamics over time by reducing the entry risk by 0.5827 and 0.5546, respectively, compared to the Tigray region. Households who currently have higher age (m_age), more cultivated land (m_Cultivated land), and a better farm asset index (m_farm asset index) are less likely to fall into poverty than their counterparts. It implies a short time to exit from their poverty compared with those who have lower age, less cultivated land, and farm asset index. Furthermore, conditions on their poverty experience when they entered the survey (M. Poverty_0), the probability of being poor for households in the previous year was poor or not poor (the entry and persistence probabilities).

Within households, there is a substantial difference between the probability of entry and exit from multidimensional poverty. Households that were nonpoor in

the initial period (indicated by the coefficient of 1. M_poverty_0) are more likely to exit and less likely to be poor than those who were poor. This infers that nonpoor households have a lower probability of multidimensional poverty in the future, and if they experience it, their exit probability is very high. This is related to the indicators used to measure multidimensional poverty. Most multidimensional poverty indicators have a long-run impact on the wellbeing of the household. For instance, once the household member is educated, the effects of their education are not only short-term but last for long (Konaté, 2010; Singh, 2016; UNESCO, 2016). In addition, as of Peña and Bacallao (2002) and Nelson (2000), nutrition has a lifelong effect on children's cognitive and physical development. Furthermore, if households have a quality house built and have enough household assets (car, radio, or refrigerators), the chance of losing these indicators and their likelihood of experiencing poverty are low unless uncontrolled coincidences occur.

4. Conclusion

The results show that a considerable share of households are multidimensionally poor, and this emanates from deprivation in living standards that include sanitation, cooking fuel, flooring made, and electricity. The result reveals that households are less deprived of child mortality. Therefore, policymakers need to prioritize the standard living dimension of poverty by focusing on the most deprived indicators of standard living dimensions.

The result of the dynamic mixed-effects probit regression shows the presence of significant dynamics of state dependence, which has a substantial and positive impact on multidimensional poverty. The current poverty status of households is positively related and significantly affected by their previous period poverty status. It also finds that households' initial poverty status is correlated with unobserved factors. The dependence ratio, cultivated land, and farm asset index are positively correlated with unobserved factors, whereas education correlates negatively with unobserved factors to multidimensional poverty.

Consistently, households that faced drought shocks and recorded high rainfall variability reported that the expected mean duration of poverty spells and the predicted steady-state probability of poverty are significantly higher for households than for their counterparts. On the other hand, the dependency ratio, education, noncultivated land, living in the Somalie and Harari regions compared with the Tigray region experience of multidimensional poverty has declined. Thus, the entry probability will decrease, and the exit probability will increase. Households, once

they experience multidimensional poverty in previous years, the exit probability is very low, while the possibility of experiencing poverty in the future is very high. Therefore, a multidimensional policy approach should target poverty reduction and sustainable development at the national and regional levels. Policies toward supporting households and intervention in programs in Ethiopia have mainly focused on rural areas. Intensifying economic empowerment, strengthening family planning programs, and increasing formal and adult education programs may be helpful for multidimensional poverty reduction in Ethiopia.

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Appendices

Appendix Table 1: Multidimensional poverty dimensions and indicators

Dimensions of poverty	Indicator	Deprived if…	Weight	Poverty line	
Education	Years of schooling	No households member has completed five years of schooling	1/6	1/18	1/3
	Child school attendance	Any school-aged child is not attending school up to class 8	1/6	1/18	
Health	Child mortality	Any child has died in the family	1/6	1/18	1/3
	Nutrition	Any child for whom there is nutritional information is malnourished	1/6	1/18	
Living standard	Electricity	The household has no electricity	1/18	1/54	1/3
	Improved sanitation	The household's sanitation facility is not improved, or it is improved but shared with other households	1/18	1/54	
	Improved drinking water	The household does not have access to improved drinking water, or safe drinking water is more than a 30-minute walk from, round-trip	1/18	1/54	
	Quality of floor	The household has a dirt, sand, or dung floor	1/18	1/54	
	Cooking fuel	The household cooks with dung, wood, or charcoal	1/18	1/54	
	Assets ownership	The household does not own more than radio-TV, telephone, bike, motorbike, or refrigerator and does not own a car or truck	1/18	1/54	
MPI(1.00)		MPI poor if deprivation at or above	1/3	1/3	

Source: Alkier and Foster (2011), Alkire, 2014, and Alkire and Santos (2014).

Appendix Table 2: Hypothesized variables to affect multidimensional poverty dynamics

Dependent variables			
Multidimensional poverty dynamics (M_ poverty)			
Variables	**Variable description and measurement**	**Unit**	**Expected sign**
Climate-induced shocks			
Production shock	Production shock (1= if households faced production shocks, 0= otherwise)	Dummy	+
Market shock	Market shock (1= if households faced production shocks, 0= otherwise)	Dummy	+/-
Drought	Self-report drought (1= if households report faced drought shocks, 0= otherwise	Dummy	+
Annual rainfall shortage	Annual rainfall shortage (1= if annual rainfall shortage, 0= otherwise)	Dummy	+/-
Growing season rainfall shortage	Growing season rainfall shortage ((1= if growing season rainfall, 0= otherwise)	Dummy	+/-
Temperature	Daily mean temperature	Degree Cilices (O_c)	+/-
Precipitation/rainfall	Mean monthly rainfall	millimeter(mm)	+/-
Annual rainfall variability	Annual rainfall variability	millimeter(mm)	+/-
Demographics factors			
Sex	Sex of households (1= if households male-headed, 0= otherwise)	Dummy	-
Age	Age of households	Continuous(year)	+/-
Family size/adult equivalent	Households size and the adult equivalent of households	Discrete/continuous (number/adult equivalent	+/-
Dependency ratio	Dependency ratio of households	Continuous (ratio)	+
Socioeconomic factors			

Education	The educational level of households	Discrete (grade)	-
Cultivated land	Cultivated land of households	Continuous Hectare)	-
Non cultivated land	Non cultivated land of households	Continuous (Hectare)	-
Farm asset index	Farm asset index of households	Continuous (index)	-
Livestock	Livestock number in tropical livestock unit	Continuous (TLU)	-
Farm income	Farm income of households	Continues (Birr)	-
Nonfarm income	Nonfarm and off-farm income of households	Continues (Birr)	-
Income from PSNP	Income from productive safety net program	Continues (Birr)	-/+
Institutional services			
Distance to market	Distance to the nearest market	Continuous (Minutes)	+
Credit service	Formal financial credit services of households (1= if households access to credit, 0= otherwise	Dummy	-
Extension access	Access to extension services of households (1= if households access to credit, 0= otherwise	Dummy	-
Geographical factors			
Residence	The residence of households (1=if households live in a rural area, 0 households live in small towns	Dummy	+
Region	The residence of the household region (1=Tigray, 2=Afar, 3=Amhara, 4=Oromia, 5=Somalie, 6=Benishangul Gumuz, 7=SNNP, 8=Gambelia, 9=Harari, and 10=Dire Dawa	Categorical	+/-

Appendix Table 3: Trends and mean difference deprivation score

Dimensions/ Indicators	2012	2014	2016	Change in 2014-2012	Change in 2016-2014	Change in 2016-2012
Education	0.148	0.143	0.139	0.005	0.004	0.008***
Years of schooling	0.059	0.054	0.049	0.004**	0.005***	0.010***
School attendance	0.089	0.089	0.090	0.000	-0.002	-0.001
Health	0.055	0.021	0.066	0.033***	-0.044***	-0.011***
Child mortality	0.016	0.017	0.062	-0.001	-0.045***	-0.046***
Nutrition	0.039	0.004	0.004	0.034***	0.001	0.035***
Living standard	0.189	0.190	0.191	-0.001	-0.001	-0.002**
Electricity access	0.046	0.044	0.044	0.002***	0.000	0.002***
Improved sanitation	0.053	0.052	0.056	0.001**	-0.004***	-0.003***
Improved water s	0.006	0.004	0.003	0.002***	0.001**	0.003***
Housing quality	0.002	0.003	0.003	-0.000	-0.001**	-0.001***
Cooking fuel	0.055	0.055	0.055	0.000	0.000**	0.001***
Asset ownership	0.026	0.032	0.030	-0.005***	0.002***	-0.003***

*** p<0.01, ** p<0.05, * p<0.1

***Observations are weighted to make results representative of all regional individuals in Ethiopia

Source: Authors' computation based on ESS (2012, 2014, 2016)

Appendix Table 4: Contribution of each dimension for each region in percentage

	2012			2014			2016			Pooled		
	Education	**Health**	**Living standard**	**Education**	**Health**	**Living standard**	**Education**	**Health**	**Living standard**	**Education**	**Health**	**Living standard**
Tigray	0.392	0.199	0.409	0.441	0.09	0.468	0.392	0.169	0.439	0.407	0.155	0.438
Afar	0.393	0.176	0.430	0.476	0.055	0.47	0.362	0.237	0.401	0.401	0.17	0.428
Amhara	0.419	0.163	0.418	0.464	0.077	0.459	0.373	0.195	0.432	0.416	0.149	0.435
Oromia	0.426	0.143	0.431	0.475	0.067	0.457	0.396	0.176	0.428	0.43	0.132	0.438
Somali	0.419	0.137	0.445	0.457	0.079	0.464	0.361	0.203	0.437	0.408	0.144	0.447
Benshag~z	0.421	0.142	0.437	0.498	0.051	0.451	0.418	0.137	0.446	0.443	0.113	0.444
SNNP	0.424	0.161	0.415	0.483	0.064	0.452	0.415	0.154	0.43	0.439	0.13	0.432
Gambela	0.438	0.080	0.481	0.508	0.033	0.459	0.354	0.217	0.429	0.428	0.117	0.455
Harari	0.433	0.168	0.399	0.476	0.086	0.438	0.377	0.229	0.394	0.421	0.172	0.407
Dire Dawa	0.443	0.139	0.418	0.499	0.067	0.434	0.389	0.227	0.384	0.438	0.153	0.409
Total	0.42	0.157	0.423	0.473	0.070	0.457	0.391	0.181	0.428	0.426	0.14	0.434

Source: Computation based on ESS (2012, 2014, and 2016)

Appendix Table 5: Climate variability variable tests by multidimensional poverty

Variables	Nonpoor	Poor	Diff	t test
Mean precipitation	1053.427	1094.890	-41.463	(-4.433)**
Mean temperature	19.320	19.406	-0.086	(-1.042)
Deviation of rainfall	-22.448	-20.858	-1.591	(-0.456)
SD of historical rainfall	106.193	105.112	1.082	(1.558)
Historical annual rainfall index	1.052	1.021	0.031*	(1.764)
Deviation of rainfall the growing season	-33.058	-32.160	-0.898	(-0.286)
Rainfall index for growing season	1.044	1.011	0.033	(1.993)**

Source: Computation based on ESS (2012, 2014, and 2016).

Appendix Table 6: Socioeconomic variables tests by multidimensional poverty

Variables	Nonpoor	Poor	Diff	t-test
Educational	7.186	5.068	2.118	(9.677)***
Adult equivalent	2.907	4.448	-1.542	(-37.295)***
Dependency ratio	0.817	1.053	-0.235	(-11.426)***
Age	47.497	45.734	1.763	(4.979)***
TLU	1.750	2.526	-0.776	(-9.841)***
Cultivated land	0.663	1.042	-0.379	(-2.872)***
Not cultivated	0.318	0.439	-0.121	(-2.401)**
PSNP	25.087	19.634	5.453	(1.406)
Farm income	6463.848	12802.539	-6338.690	(-1.489)
Non/off farm income	1101.149	414.781	686.368	(3.231)***
Farm asset index	-0.173	-0.244	0.071***	(4.023)***
Distance to market	64.767	66.977	-2.210*	(-1.893)*

Source: Computation based on ESS (2012, 2014, and 2016).

Appendix Table 7: Additional statistics on poverty transition and probability

Variable	Transition	Probability
L.M_poverty (=1)	Entry probability P(1/0)	0.6411
	Exit probability P(0/1)	0.2281
	T in y=1/Steady state Pr.	0.7376
	Mean duration	4.3840
1.M_poverty_0	Entry probability P(1/0)	0.6401
	Exit probability P(0/1)	0.2237
	T in y=1/Steady state Pr.	0.7410
	Mean duration	4.4696
Drought shock(yes)	Entry probability P(1/0)	0.7038
	Exit probability P(0/1)	0.1784
	T in y=1/Steady state Pr.	0.7978
	Mean duration	5.6063
Mean rainfall/precipitation (1083.924 mm)	Entry probability P(1/0)	0.6404
	Exit probability P(0/1)	0.2280
	T in y=1/Steady state Pr.	0.7375
	Mean duration	4.3867
Age	Entry probability P(1/0)	0.6369
	Exit probability P(0/1)	0.2339
	T in y=1/Steady state Pr.	0.7314
	Mean duration	4.2758
Adult equivalent	Entry probability P(1/0)	0.6469
	Exit probability P(0/1)	0.2120
	T in y=1/Steady state Pr.	0.7532
	Mean duration	4.7169
Education	Entry probability P(1/0)	0.6421
	Exit probability P(0/1)	0.2260
	T in y=1/Steady state Pr.	0.7396
	Mean duration	4.4241
Dependency ratio (0.99)	Entry probability P(1/0)	0.6423
	Exit probability P(0/1)	0.2276
	T in y=1/Steady state Pr.	0.7383
	Mean duration	4.3932
Cultivated land (0.94)	Entry probability P(1/0)	0.6408
	Exit probability P(0/1)	0.2276
	T in y=1/Steady state Pr.	0.7380
	Mean duration	4.3947
Noncultivated land (0.407)	Entry probability P(1/0)	0.6403
	Exit probability P(0/1)	0.2283
	T in y=1/Steady state Pr.	0.7372
	Mean duration	4.3802

Farm asset index	Entry probability P(1/0)	0.6542
	Exit probability P(0/1)	0.2209
	T in y=1/Steady state Pr.	0.7476
	Mean duration	4.5276
PSNP income	Entry probability P(1/0)	0.6406
	Exit probability P(0/1)	0.2282
	T in y=1/Steady state Pr.	0.7374
	Mean duration	4.3827
Access to extension services(yes=1)	Entry probability P(1/0)	0.6698
	Exit probability P(0/1)	0.2040
	T in y=1/Steady state Pr.	0.7666
	Mean duration	4.9025
Access to credit (yes=1)	Entry probability P(1/0)	0.6971
	Exit probability P(0/1)	0.1837
	T in y=1/Steady state Pr.	0.7915
	Mean duration	5.4443
Residence (rural=1)	Entry probability P(1/0)	0.6489
	Exit probability P(0/1)	0.2204
	T in y=1/Steady state Pr.	0.7465
	Mean duration	4.5372
Afar	Entry probability P(1/0)	0.7151
	Exit probability P(0/1)	0.1697
	T in y=1/Steady state Pr.	0.8082
	Mean duration	5.8930
Somalie	Entry probability P(1/0)	0.5827
	Exit probability P(0/1)	0.2754
	T in y=1/Steady state Pr.	0.6791
	Mean duration	3.6316
Gambela	Entry probability P(1/0)	0.5546
	Exit probability P(0/1)	0.2997
	T in y=1/Steady state Pr.	0.6492
	Mean duration	3.3362
Dire Dawa	Entry probability P(1/0)	0.7327
	Exit probability P(0/1)	0.1567
	T in y=1/Steady state Pr.	0.8238
	Mean duration	6.3820

Source: Computation based on ESS (2012, 2014, and 2016)

Appendix Table 8: Probability of entry and persistence in multidimensional poverty

Variable	Prob.	Std. Err.	P>z	Lower CI	Upper CI
Lag multidimensional poverty (1 L.M_poverty) = 1, Yes					
$\boldsymbol{P(1\|0)}$	0.6411	0.0126	0.0000	0.6164	0.6659
$\boldsymbol{P(1\|1)}$	0.7719	0.0070	0.0000	0.7582	0.7856
Initial based of multidimensional poverty (1.M_povert_0)					
$\boldsymbol{P(1\|0)}$	0.6401	0.0131	0.0000	0.6145	0.6658
$\boldsymbol{P(1\|1)}$	0.7763	0.0067	0.0000	0.7632	0.7893
Drought shock = 1, Yes					
$\boldsymbol{P(1\|0)}$	0.7038	$\boldsymbol{P(1\|0)}$	0.7038	$\boldsymbol{P(1\|0)}$	0.7038
$\boldsymbol{P(1\|1)}$	0.8216	$\boldsymbol{P(1\|1)}$	0.8216	$\boldsymbol{P(1\|1)}$	0.8216
Mean rainfall/precipitation (1083.924 mm)					
$\boldsymbol{P(1\|0)}$	0.6404	0.0126	0.0000	0.6156	0.6651
$\boldsymbol{P(1\|1)}$	0.7720	0.0070	0.0000	0.7583	0.7858
Age (mean= 46.2)					
$\boldsymbol{P(1\|0)}$	0.6369	0.0126	0.0000	0.6121	0.6616
$\boldsymbol{P(1\|1)}$	0.7661	0.0077	0.0000	0.7511	0.7811
Adult equivalent (mean=4)					
$\boldsymbol{P(1\|0)}$	0.6469	0.0142	0.0000	0.6191	0.6747
$\boldsymbol{P(1\|1)}$	0.7880	0.0072	0.0000	0.7738	0.8022
Education (mean=5.63)					
$\boldsymbol{P(1\|0)}$	0.6421	0.0126	0.0000	0.6174	0.6669
$\boldsymbol{P(1\|1)}$	0.7740	0.0071	0.0000	0.7601	0.7878
Dependency ratio (0.99)					
$\boldsymbol{P(1\|0)}$	0.6423	0.0125	0.0000	0.6177	0.6669
$\boldsymbol{P(1\|1)}$	0.7724	0.0070	0.0000	0.7588	0.7860
Cultivated land (0.94)					
$\boldsymbol{P(1\|0)}$	0.6408	0.0126	0.0000	0.6160	0.6656
$\boldsymbol{P(1\|1)}$	0.7725	0.0070	0.0000	0.7587	0.7862
Noncultivated land (0.407)					
$\boldsymbol{P(1\|0)}$	0.6403	0.0126	0.0000	0.6155	0.6650
$\boldsymbol{P(1\|1)}$	0.7717	0.0070	0.0000	0.7580	0.7854
Farm asset index (mean= -0.225)					
$\boldsymbol{P(1\|0)}$	0.6542	0.0126	0.0000	0.6295	0.6789
$\boldsymbol{P(1\|1)}$	0.7791	0.0069	0.0000	0.7656	0.7927
PSNP income (21.076)					
$\boldsymbol{P(1\|0)}$	0.6406	0.0126	0.0000	0.6159	0.6653
$\boldsymbol{P(1\|1)}$	0.7718	0.0070	0.0000	0.7581	0.7855

Access to extension services (yes=1)					
$\boldsymbol{P}(\mathbf{1}\|\mathbf{0})$	0.6698	0.0152	0.0000	0.6400	0.6996
$\boldsymbol{P}(\mathbf{1}\|\mathbf{1})$	0.7960	0.0098	0.0000	0.7769	0.8152
Access to credit (yes=1)					
$\boldsymbol{P}(\mathbf{1}\|\mathbf{0})$	0.6971	0.0243	0.0000	0.6495	0.7447
$\boldsymbol{P}(\mathbf{1}\|\mathbf{1})$	0.8163	0.0180	0.0000	0.7811	0.8516
Residence (rural=1)					
$\boldsymbol{P}(\mathbf{1}\|\mathbf{0})$	0.6489	0.0130	0.0000	0.6234	0.6744
$\boldsymbol{P}(\mathbf{1}\|\mathbf{1})$	0.7796	0.0073	0.0000	0.7653	0.7939
Afar					
$\boldsymbol{P}(\mathbf{1}\|\mathbf{0})$	0.7151	0.0340	0.0000	0.6485	0.7816
$\boldsymbol{P}(\mathbf{1}\|\mathbf{1})$	0.8303	0.0251	0.0000	0.7812	0.8795
Somalie					
$\boldsymbol{P}(\mathbf{1}\|\mathbf{0})$	0.5827	0.0328	0.0000	0.5185	0.6470
$\boldsymbol{P}(\mathbf{1}\|\mathbf{1})$	0.7246	0.0262	0.0000	0.6732	0.7760
Gambella					
$\boldsymbol{P}(\mathbf{1}\|\mathbf{0})$	0.5546	0.0378	0.0000	0.4806	0.6286
$\boldsymbol{P}(\mathbf{1}\|\mathbf{1})$	0.7003	0.0327	0.0000	0.6361	0.7644
Dire Dawa					
$\boldsymbol{P}(\mathbf{1}\|\mathbf{1})$	0.7327	0.0315	0.0000	0.6710	0.7945
$\boldsymbol{P}(\mathbf{1}\|\mathbf{1})$	0.8433	0.0225	0.0000	0.7991	0.8875

Source: Computation based on ESS (2012, 2014, and 2016)

Choice of Market Outlet and Its Effect on Market Gain of Smallholder Potato Farmers in Eastern Ethiopia

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Abstract

The aim of this study was to figure out choice of market outlet by small holder potato growers and its effect on their market gain in eastern Ethiopia. The study was carried out in two selected woredas (Haramaya and Kombolcha) of Eastern Hararghe Zone of Ethiopia. For this study, sample of 300 potato growing farm households were selected proportionally from 6 Kebelles. The collected data from the selected sample households was analyzed using descriptive and multi-variate probit econometric model analysis. Findings of the study reveals that most of the potato farm households use collectors only, wholesalers only or both as outlet for marketing of their produce. No matter the fact that selling via cooperatives can bring about better market gain, very few farm households were able to sale their produce through this channel due to its limited operational capacity. The study also shows that age, education, and work experience of the household head, farm size, total output of potato, proportion of farm income, contractual relation, membership to cooperatives, mode of payment and distance to the nearest market were found to be the factors that determine the choice of market outlet. Findings of the study indicate that it would be better to improve the outreach and operational capacity of the agricultural cooperatives. Besides, provision of better trainings related to marketing contractual arrangements is crucial as contractual arrangement is among the significant variables to choose cooperatives as market outlet. Frequent extension service is also among the crucial elements to improve the use of cooperatives as market outlet. Multiple choices of market outlets including cooperatives, wholesalers and collectors can also be recommended to enhance the market gain of the farm households.

Kew words: Choice, Market outlet, Market Gain, Multi-Variate Probit, Determinants

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1. Introduction

African countries' experience indicates that the agricultural research and development organizations have made significant progress on increasing agricultural productivity. But, sustainability of productivity and growth of the agricultural sector depends on expansion of market opportunities (Eleni and Haggblade, 2004). Hence, it is now increasingly evident that smallholder farmers' key concern is not only agricultural productivity and household food consumption, but also increasing better market access. Agricultural research and development organizations are now under pressure to shift from enhancing productivity of food crops to improving profitability and competitiveness of small-scale farming, and linking smallholder farmers to more profitable markets (Njuki *et al.,* 2015). In this regard, selection of better market outlet is believed to be crucial element for the smallholder farmers.

Keeping this in mind, as vegetables are among the widely grown cash crops in the study area, improving the market gain of the farm households from vegetables market has a paramount importance. In eastern part of Ethiopia, especially Eastern Hararghe, production of vegetables by smallholder farmers is highly substantial. Hence, apart from improving the productivity of vegetables in the region, access to better market, from which justifiable benefit is generated, is inevitable if sustainable development of the smallholder farmers is to be targeted on.

In the region, of vegetables, potato production takes the largest share (more than 60%) in some areas such as Kombolcha and Haramaya (Abraham, 2013; Piguet, 2003). There are several evidences showing that Hararghe, in eastern Ethiopia, is one of the major potato producing regions of the country and potato is grown in both the rainy and dry season. The presence of regional and domestic markets around nearby cities as well as exports to neighboring countries such as Djibouti and Somalia have contributed to the development of potato production in Hararghe highlands (Adane *et al*., 2010).

No matter the fact that potato has become an increasingly important crop and contributes for food security, employment, nutrition and development in the socio-economic status of producers, the extent of benefit generated from the market is possibly determined by the farmers' choice of market outlet. Abate *et al*., (2019) states that market outlet choice is one of the most important farm household decisions to sell their produce in different marketing outlets and has a great impact on household income. In order to maximize the benefits that they may earn, farmers have to make appropriate decisions as to where they should sell their product.

Marketing channel, as defined by Stern *et al*. (1996), is a set of interdependent organizations involved in the process of making a product or service available for consumption or use. Makhura (2001) inspected that the marketing of smallholder farmers was constrained by poor infrastructure, distance from the market, lack of own transportation and inadequate market information. Lack of bargaining power along with various credit bound relationships with the buyers has led to farmers being exploited during the transaction where most of the farmers become price takers. The majority of farmers are smallholders and hence, unable to obtain a fair price for their produce and resulting not being able to sustain their livelihood (Xaba and Masuku, 2013).

Market outlet choices are household-specific decision and several drivers have to be considered as a basis for such decision (Abate *et al*, 2019). There are various factors that may affect the farmers' choice of market outlet to provide their produce to the market. Hence, identifying these factors is very important for possible areas of interventions that may help farmers to maximize their benefits from the market.

In this regard, there are very few studies undertaken in the area on the specified crop, of which Bezabih *et al* (2015) is the prominent one. However, their study doesn't look into the relationship among the given choices of market outlets, for which they applied multinomial logit model which is inappropriate if choices are interdependent. To solve this problem, they used combination of choices as one choice variable which doesn't clearly enable to identify the factors for each specific choice. Besides, they didn't figure out which market outlet is better in terms of the net market gain generated.

Therefore, this study intends to fill these gaps through application of multivariate probit model to identify the major factors affecting the choice of market outlet of the farm households, which takes into account the possible interdependence among the choices of market outlet, as well as making comparative analysis for the net market gain generated across each market outlet.

2. Materials and Methods

2.1 Description of the Study Area

East Hararghe is one of the Zones of the Region of Oromia found in Eastern part of Ethiopia. East Hararghe takes its name from the former province of Hararghe. East Hararghe is bordered on the southwest by the Shebelle River which separates it from Bale, on the west by Western Hararghe, on the north by Dire Dawa and on the

north and east by the Somali Region. The Harari Region is an enclave inside this zone. The Administrative center of this zone is Harar.

In eastern Hararghe (Oromia region), all types of agro-ecological zones (Kola, Dega and Weyna Dega) exist having both highland and lowland societies. The mean annual rainfall varies from lowland to highland. It has two rainy seasons for agricultural production which are known to be "Belg[5]" and "Meher[6]" seasons. Output is expected to be higher immediately after these seasons than after the dry seasons including "Bega[7]" and "Tseday[8]" seasons. Hence, prices of the produce are expected to show ups and downs across these seasons and places (UNDP-EUE, 1994).

Based on the 2007 Census conducted by the Central Statistical Agency of Ethiopia (CSA), this Zone has a total population of 2,723,850, an increase of 48.79% over the 1994 census, of whom 1,383,198 are men and 1,340,652 women; with an area of 17,935.40 square kilometers. East Hararghe has a population density of 151.87. While 216,943 or 8.27% are urban inhabitants, a further 30,215 or 1.11% are pastoralists. A total of 580,735 households were counted in this Zone, which results in an average of 4.69 persons to a household, and 560,223 housing units.

The picture in Eastern Hararghe zone shows that production is based on roughly 70% crops and 30% on livestock. Major cash crops grown in Eastern Hararghe include khat, coffee, onion, haricot beans, groundnuts, mangos, sweet potato, potatoes and other types of fruits and vegetables. Generally, the dominant cash crops in the area were found to be khat, coffee and vegetables (UNDP-EUE, 1994).

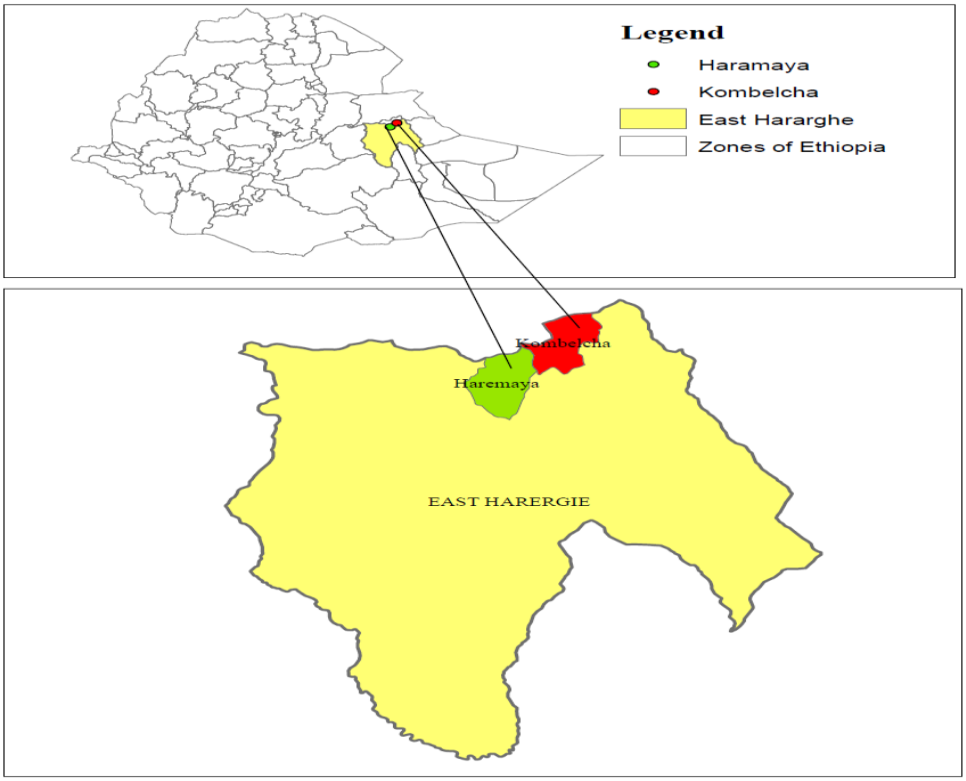
Of vegetables, potato production takes the largest share (more than 60%) in some areas such as Kombolcha and Haramaya (Abraham, 2013; Piguet, 2003). Hararghe, in eastern Ethiopia is one of the major potato producing regions of the country and potato is grown in both the rainy and dry season. The presence of regional and domestic markets around nearby cities as well as exports to neighboring countries such as Djibouti and Somalia have contributed to the development of potato production in Hararghe highlands (Adane *et al*., 2010).

The woredas found in East Hararghe zone include Fedis, Babile, Jarso, Kombolcha, Kersa, Haramaya, Meta, Deder, Gursum, Kurfachele, Gorogutu,

[5] Belg (authumn) covers months from March to May which is known to be the shorter growing season. This season is with occasional showers. May is the hottest month in Ethiopia.
[6]Meher (Summer) is the most rainy season that covers months of June, July and August.
[7] Bega (Winter) covers December, January and February which is the dry season with frost in morning specially in January.
[8] Tseday covers September, October and November which is sometimes known as the main harvest season.

Bedeno, and Garamuleta. From these woredas, Haramaya and Kombolcha were selected as the study areas since these areas are the major producers and suppliers to local and export markets. Map of the study areas is shown using figure 1.

Figure 1: Geographical location of the study areas



Data Type, Sources and Methods of Data Collection

The type of data required to undertake this study is cross-sectional. Sources of data for this inquiry are both primary and secondary. The primary data was collected using survey on farm households whereas the secondary data were extracted from books, articles, and published and unpublished documents of offices of agriculture and cooperatives. The primary method of data collection in this study was using questionnaires. To this end, 12 Development Agent (DA) workers were recruited as enumerators for the data collection. Besides, Focus Group Discussions (FGDs) were held with figurative people in the area and concerned officials from offices of Agriculture and Cooperatives were taken as key informants.

Sampling Procedure

In this study, mixed sampling method was applied. In the first stage, the two Woredas (Haramaya and Kombolcha) were selected as specific study areas purposively as these are the major suppliers of the crop. In the second stage, four Kebeles (which are much closer to irrigation for production of vegetables including potato[9]), from which the farm households are drawn, were purposively selected based on consultation with expertise from Offices of Agriculture of the two Woredas. These four clusters include: Tinike, Tuji Gabisa, Kerensa, and Bilisuma. In the third stage, the farm households were randomly selected (from both members and non-members of cooperatives) using probability proportional to size (PPS) sampling.

The sample size was determined using the finite population correction factor following Smith (2013). The formula for the sample size determination is specified as:

$$n = \frac{n_0 N}{n_0 + (N+1)} \qquad where \qquad n_0 = \frac{Z^2 P(1-P)}{e^2}$$

Where: $n\ is\ the\ sample\ size\ taken\ for\ the\ study$

$Z\ is\ 1.96\ (for\ 95\%\ confidence\ level)$

$n_0\ is\ the\ sample\ size\ without\ considering\ the\ finite\ correction\ factor$

$P\ is\ 0.5\ (for\ proportion)$

$e\ is\ 0.06\ (for\ margin\ of\ error)$

$N\ is\ 4712\ (the\ study\ population\ of\ the\ selected\ kebeles)$

Hence n was found to be 253. However, in consideration of non-response rate of 18%, the sample size was raised to 300. Accordingly, the total sample size taken for the study is 300. The detail of the sample size distributed for the Kebeles, by using PPS, is presented as follows.

Table 1: Distribution of the samples across kebeles

Wereda	Kebelle	Population	Sample
Haramaya	Tinike	600	34
	Tuji Gabisa	1353	87
Kombolcha	Kerensa	1323	85
	Bilisuma	1436	94
Total		4712	300

[9] Potato/vegetable growers are those having better irrigation access

Method of Data Analysis

To undertake this study, descriptive statistics and inferential statistics including econometric model were used to analyze the collected data. The descriptive statistics was used to present the frequency of choice of market outlet by the sample farm households for each market outlet. Inferential statistics (which involves Wilks' Lambda, Pillai's Trace, Lawley-Hotelling Trace and Roy's Largest Root) was employed in order to compare the net per unit market gain[10] generated by the farmers across the market outlets. The market outlets found in the study area, for the farm households, include agricultural cooperatives, wholesalers, collectors and retailers. The econometrics model involves multivariate probit model which was applied so as to identify the major determinants of choice of market outlet by the farm households. This was presented in detail as follows.

Determinants of farmers' choice of market outlet

Analysis of factors affecting choice of market outlet is usually carried out making use of multinomial logit regression provided that there are more than two choices provided to the farmer (Lijia and Xuexi, 2015; Berhanu *et al*., 2013; Xaba and Masuku, 2013; and Abraham, 2013).

However, there are also studies which consider only two choices of market channels to make such analysis; for which, they apply binary choice regression models. These studies usually focus on identifying the driving factors that induce or prohibit the use of market cooperatives as a way of market outlet for farmers' produce. For instance, Anteneh *et al*. (2011) have used Tobit regression model to identify these factors for coffee market in Sidama zone. In their study, two choices of market channel: private traders and market cooperatives were considered.

In our case, there are more than two choices of market channel provided to the farmers. Hence, the relevant model that has to be considered for this study should be unordered response discrete choice model. In this regard, there are five major alternative models from which we need to select one based on our point of interest. These include multinomial logit model, multinomial probit model, nested logit model, mixed logit model and multivariate probit model.

Multinomial logit model is widely applied by researchers, to deal with such a case, due to its simplicity as compared to the other models. This model provides

[10] Net per unit market gain in this study refers to the difference between per unit revenue generated from yearly sale of potato and per unit marketing cost (which include costs for sacking, transportation, brokers, loading/unloading, membership fee for cooperatives and others).

the probability of choosing an alternative based on logistic distribution and assumption of linear utility function of observable characteristics through maximum likelihood estimation. No matter its simplicity, its application relies on fulfillment of the assumption of Independence of Irrelevant Alternatives (IIA). This refers to the assumption that the ratio of probabilities of two alternative choices should not depend on other alternative choices (Verbeek, 2004). In addition, this model does not take into account the possibility of making multiple choices among alternatives. Hence, this model cannot be applicable for our case.

While it is possible to relax the IIA property, this generally leads to (conceptually and computationally) more complicated models (Verbeek, 2004). Multinomial probit model, nested logit model, and mixed logit model are among the models that can be used to coup-up with the problem of IIA property. However, these models are also relevant only if a single choice is made among alternatives; they do not take into account the possibility of choosing more than one alternative (Green, 2003).

In cognizant of this, for this study, we have applied the multivariate probit model to determine the factors affecting choice of market outlet for the farmers. Multivariate probit model is used when there is more than one discrete outcome which is expressed by multiple equations reflecting choices between multiple pairs of alternatives. This model is a natural extension of the probit model that allows more than one equation, with correlated disturbances, in the same sprit as seemingly unrelated regressions model (Green, 2003).

This model is assumed to be framed based on multiple binary equations. The structural equation for the model based on latent variable (representing utility of individual i from alternative t) is expressed as (Greene, 2003):

$$y^*_{it} = x'_{it}\beta + \varepsilon_{it}, \quad y_{it} = 1 \text{ if } y^*_{it} > 0, \text{ 0 otherwise, } i = 1, \ldots\ldots, n; t = 1, \ldots\ldots, T \quad \textbf{(1)}$$

Where: y^*_{it} is a vector of latent variables showing the threshold of choosing alternative t, y_{it} is the choice variable of choosing alternative t, x'_{it} represents vector of explanatory variables, β is vector of estimators, and ε_{it} is vector of error terms which are distributed as multivariate normal distribution with zero means, unitary variance and n x n contemporaneous correlation matrix R = [ρ_{ij}], with density $\phi(\varepsilon_{i1}, \varepsilon_{i2}, \ldots\ldots, \varepsilon_{it}; R)$ (Lin *et al.*, 2005). Here, we should note that the number of

binary equations is T. In our case, this represents the number of market outlets which include use of cooperatives, wholesalers, collectors and retailers; hence T = 4.

$$y_i = \begin{cases} 1 \; if y_i^* > 0 \\ 0 \; otherwise \end{cases} \qquad i = 1, 2, \ldots . 4 \qquad \textbf{(2)}$$

Following Lin *et al*. (2005), the likelihood contribution for an observation is the t-variate normal probability function given by:

$$\Pr(y_1 = 1, y_2 = 1, \ldots\ldots, y_t = 1 / x) = \int_{-\infty}^{(2y_1-1)x'\beta_1} \int_{-\infty}^{(2y_2-1)x'\beta_2} \ldots \times \int_{-\infty}^{(2y_t-1)x'\beta_t} \phi(\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_t; Z'RZ) d\varepsilon_t .. d\varepsilon_2 d\varepsilon_1 \qquad \textbf{(3)}$$

Where Z = diag[$2y_1 - 1, \ldots, 2y_t - 1$]. The maximum likelihood estimation maximizes the sample likelihood function, which is a product of probabilities (3) across observations.

$$\Pr(y_i = 1) = \Phi(x'\beta_i), \;\; i = 1, 2, \ldots \ldots . . t \qquad \textbf{(4)}$$

To quantify the marginal effects of explanatory variables, the probability of choice of each market outlet can be differentiated, where Φ(.) is the univariate standard normal cumulative distribution function. Because all explanatory variables are binary, the effects of each variable on the choice probability (4) are calculated by simulating a finite change in the variable (i.e., from0 to 1) while holding all other variables at the sample means.

The marginal effects of explanatory variables on the propensity to choose a given channel are calculated as:

$$\partial P_t / \partial x = \phi(x'\beta)\beta_t, t = 1, 2, \ldots, T \qquad \textbf{(5)}$$

Where: P_t is the probability of choosing channel t, $\phi(.)$ is the standard univariate normal cumulative density distribution function (Hassan, 1996).

Summary of description of variables to be considered for the multinomial logit model is stated in Table 2. Definition of the variables and hypothesis of the relationship between the explanatory and the dependent variables is explained as follows:

Choice of market channel: This is the dependent variable showing choice of market outlet by the farmers. It is a multiple discrete variable with two alternatives each, which include: choosing cooperatives or not (denoted by 1 and 0, respectively); choosing wholesalers or not (denoted by 1 and 0, respectively); choosing collectors or not (denoted by 1 and 0, respectively) and choosing retailers or not (denoted by 1 and 0, respectively).

Sex of household head: This variable is an independent dummy variable with two categories including female (denoted by 0) and male (denoted by 1). Male headed households are assumed to have more production advantages over females since female are often constrained by lack of capital and poor access to institutional credit and extension service (Tanga *et al.*, 2000). Hence, male headed households are supposed to be more market oriented which led them to prefer multiple market outlets to provide their produce to the market.

Age of the household head: This is a continuous independent variable measured in years. Younger age household heads are expected to prefer to provide their produce to the market through private traders than cooperatives (Xaba and Masuku, 2013). This is because young aged household heads tend to produce and sell more than older aged household heads (Tshiunza *et al*., 2001).

Education level of the household head: This is a dummy independent variable with values of 0 and 1 for illiterate and literate, respectively. Education is believed to make the farmers engage with better decisions. This is because education plays an important role in adoption of new technologies and believed to improve readiness of the head to accept new ideas and innovations. Besides, it enables the head to get updated demand and supply information (Berhanu *et al.*, 2013).

Experience of the household head in potato production: This is a continuous independent variable measured in the number of years a household has been engaged in potato production. Households who have been engaged in potato production and marketing are expected to have more experiences regarding opportunities and challenges of the production, processing and marketing. Hence, household heads with more experience of potato production are expected to better decision of market outlet to provide their produce to the market.

Farm size: This is a continuous independent variable measured in hectare. Farmers with large farm size are expected to have large amount of production which may be beyond the buying capacity of cooperatives which lead them to sell to private traders (Anteneh *et al*., 2011).

Risk of lack of demand: This is an ordered independent variable showing the extent of risk averseness of the farmers, which is measured in Likert scale ordered

from very low to vary high. The order is stated as very low (denoted by 0), low (denoted by 1), moderate (denoted by 2), high (denoted by 3), and very high (denoted by 4). It is hypothesized that more risk averse farmers prefer to provide their produce to the market through cooperatives, since cooperatives were established for such kind of purposes.

Geographical location (woreda): This is a categorical independent variable representing the location of the two wordas on which the survey was made (i.e. Haramaya denoted by 1 and Kombolcha denoted by 0). There is no any theoretical base to make hypothesis for this variable.

Proportion of farm income: This is a continuous independent variable measured in ratio of farm income to total income of the farmers. It is expected that farmers with less diversified proportion of income (large proportion of farm income) normally are risk averse so that they likely to sell their produce less lucrative market because their primary goal is to find better demand (Anteneh *et al*., 2011).

Mode of payment: This is an ordered variable independent variable showing the way payment is made to the farmers when they sell their produce (i.e. payment not on credit (on cash) denoted by 1, partially on credit is denoted by 2, and on credit (not on cash) is denoted by 3). Most households need cash from sale of their produce. Hence, it is expected that sale on cash make farmers to sell to private traders and cooperatives (Staal *et al*., 2006).

Quantity of output sold: This is a continuous independent variable measured in kg. As the quantity of output sold is higher, there is possibility of higher market surplus beyond the taking capacity of cooperatives (Anteneh *et al*., 2011). Hence it is expected that farmers with higher level of quantities to be sold prefer to provide their produce to private traders.

Access to credit: This is a dummy independent variable showing the provision of credit for the farmers (i.e. having access denoted by 1 and with no access denoted by 0). Farmers who do have access to credit, produce more production beyond the buying capacity of cooperatives and will sell to other competitors or private traders (Anteneh, *et al*., 2011).

Access to market information: This is an ordered independent variable (i.e. having very low access denoted by 1, low access denoted by 2, moderate access denoted by 3, higher access denoted by 4 and very higher access denoted by 5). Better market information raises the likelihood of market participation of households (Goetz, 1992). Therefore, it is expected that farmers with better market access prefer better market outlet to sell their produce.

Frequent access to extension service: This is a dummy independent variable (i.e., having access denoted by 1 and with no access denoted by 0). It is expected that access to extension service widens knowledge of use of improved technologies and impacts market outlet choices (Lerman, 2004). Hence, it can be hypothesized that better access to extension service intends to make farmers engage with better market outlet.

Table 2: Description of variables to be considered for the multivariate probit model

Name of the variable	Type of the variable	Description
(Dependent Variable) Choice of market channel	Multiple Dummy	Choosing cooperatives = 1, 0 otherwise Choosing wholesalers = 1, 0 otherwise Choosing collectors = 1, 0 otherwise Choosing retailers = 1, 0 otherwise
Sex of household head	Dummy	Female = 0, male = 1
Age of the household head	Continuous	Continuous
Education/literacy	Dummy	Illiterate = 0, literate = 1
Experience (in years) of the household head in potato production	Continuous	Continuous
Family size	Continuous	Continuous
Farm size	Continuous	Continuous
Risk of lack of demand	Ordered	Very low = 0, low = 1, moderate = 2, high = 3, very high = 4
Geographical location (Woreda)	Dummy	Haramaya = 1, Kombolcha = 0
Proportion of farm income	Continuous	Continuous
Mode of payment	Ordered	Not on credit = 1, partially on credit = 2, totally on credit = 3
Quantity of output sold	Continuous	Continuous
Access to credit	Dummy	Has no access = 0, has access = 1
Access to market information	Ordered	very low access = 1, low access = 2, moderate access = 3, higher access = 4 and very higher access = 5
Access to extension services	Dummy	Not provided = 0, provided = 1
Membership in cooperatives	Dummy	Not member = 0, member = 1
Marketing agreement	Ordered	Not contracted = 0, Partially Contracted = 1, Fully contracted = 2
Distance to the nearest urban	Continuous	Continuous

Membership to cooperatives: This is a dummy independent variable (i.e. being a member denoted by 1 and not being a member denoted by 0). It is obvious that households who are member of cooperatives are supposed to sell their produce to cooperatives.

Marketing agreement: This is an ordered independent variable showing the extent of contractual agreement made between farmers and buyers (i.e., no contractual agreement denoted by 1, partial contractual agreement denoted by 2 and full contractual agreement denoted by 3). Contractual agreement is often made between farmers and cooperatives and largescale private traders (Xaba and Masuku, 2013). Hence, it is expected that non-contractual sell is made to retailers.

Distance to the nearest urban center: This is a continuous independent variable measured in km. If households are closer to the nearest urban center, they face lesser transportation cost and loss due to spoilage. Besides, they generate better market information (Berhanu *et al*., 2013). This will lead them to be more market oriented. However, if they are far away from such a market, they need to sell their produce to cooperatives.

Results and Discussion

Descriptive and Simple Inferential Analysis

Result of the frequency of choice of each market outlet from the total sample farm households was presented in table 3. Noting that multiple market outlet choices can be made by the potato farm households, as indicated in the table, collectors were found to be the dominant choice of market outlet (which were chosen by 57% of potato farm households) followed by wholesalers (which were chosen by 56% of the farm households).

Table 3: Choice of market outlet by the potato farm households

Market Outlet	Chosen		Not chosen		Total	
	Freq.	Per.	Freq.	Per.	Freq.	Per.
Cooperatives	58	19.33	242	80.67	300	100
Wholesalers	169	56.33	131	43.67	300	100
Collectors	171	57.00	129	43.00	300	100
Retailers	37	12.33	263	87.67	300	100

Source: Own computation, 2020

Cooperatives were chosen as market outlet by only 19% of the potato farm households. This clearly reflects the relatively lower outreach of cooperatives for the potato farm households as choice of market outlet. Retailers are chosen as market outlet by only 12% of the farm households implying that they are the rare choice of market outlet.

In consideration of the existence of multiple choice of the potato farm households, the possibilities of the combinations of the choices along with their frequency are presented using table 4. There are 15 possibilities of the combination of the choices, as shown in the table, of which, there are no farm households choosing the fourth (choosing cooperatives and retailers), the sixth (choosing cooperatives, collectors and retailers) and the eighth (cooperatives, wholesalers, collectors and retailers) combinations. From the 15 combinations of market outlet choices, choosing collectors only takes the largest share of choice (with 31% share), which is followed by wholesalers only (with 25% share) and wholesalers and collectors (with 14% share).

Table 4: Combinations of market outlet choice possibilities and their frequency

S/N	Market Outlet Choice Possibilities	Frequency of Choice	Percentage
1	Cooperatives only	11	0.04
2	Cooperatives and wholesalers	14	0.05
3	Cooperatives and collectors	15	0.05
4	Cooperatives and retailers	0	0.00
5	Cooperatives, wholesalers and collectors	14	0.05
6	Cooperatives, collectors and retailers	0	0.00
7	Cooperatives, wholesalers and retailers	4	0.01
8	Cooperatives, wholesalers, collectors and retailers	0	0.00
9	Wholesalers only	74	0.25
10	Wholesalers and collectors	43	0.14
11	Wholesalers and retailers	18	0.06
12	Wholesalers, collectors and retailers	2	0.01
13	Collectors only	92	0.31
14	Collectors and retailers	5	0.02
15	Retailers only	8	0.03
	Total	300	100

Source: Own computation, 2020

The choice of market outlet has its own implication on the net market gain of the farm households. Smallholder farmers sell their produce for one or more

combination of market outlets depending on their objectives and availability of market outlets. One of their objectives might be earning higher income (Marelign *et al*, 2019). In this study, attempts were made to compare the net market gain that can be generated from each market outlet. To this end, average price of each seller and all the possible marketing costs (including costs for sacking, transportation, brokers, loading/unloading, storage, fees and other related costs) were taken into consideration.

As indicated in table 5, means of net gains that can be generated from each choice of market outlet were compared for their equality using tests of Wilks' Lambda, Pillai's Trace, Lawley-Hotelling Trace and Roy's Largest Root. Results of these statistics reveal that the mean net gains are not equal significantly. Using cooperatives only as market outlet has the highest mean of net gain for the farm households.

This can be an indication that market outlet via cooperatives may help the farmers generate better price or reduce their costs of marketing. Farmers who sell their produce via cooperatives union can have better market access and better price (Alemu, 2011), as well as the existence of contracts, flexibility and trust can reduce costs of marketing via cooperatives (Zoltan *et al*, 2012).

Table 5: Comparison of net market gain across market outlets Market Outlet Choice

Summary of Per Unit Net Market Gain			
	Mean	**Std. Dev.**	**Frequency**
Cooperatives Only	6.4144289	1.2484056	11
Wholesalers Only	5.664407	1.1567654	74
Collectors Only	5.6662611	0.99317239	92
Retailers Only	5.3812501	1.8589432	8
Any Combination	5.4531712	0.79313119	115
Total	5.6039518	1.0178922	300
Test For Equality of 5 Group Means			
	Statistic	**F-value**	**Prob>F**
Wilks' Lambda	0.9649	2.68	0.0319
Pillai's Trace	0.0351	2.68	0.0319
Lawley-Hotelling Trace	0.0363	2.68	0.0319
Roy's Largest Root	0.0363	2.68	0.0319

Source: Own computation, 2020

However, due to the limited operational capacity of the cooperatives only small number of farmers are enjoying this benefit, in the study area. The rest of the

market outlets can be ranked in descending order based on their relative mean of net gain as: collectors only, wholesalers only, any combination of the market outlets, and retailers only.

In order to know the benefit of the choice of each combination of market outlets, what was mentioned above as "any combination" was segregated into all the possible combinations thereby each one's net market gain was computed and compared. This is presented using table 5. As indicated in table 6, the test of the equality of the mean net gain across all the combinations of choices reveal significant difference of the mean. The result shows that choosing cooperatives only and choosing the combination of "cooperatives, wholesalers and collectors" are able to provide higher net market gain than the rest combinations of choices. The result also shows that choosing the combinations of "cooperatives and wholesalers", "wholesalers only", and "collectors only" as market outlet can provide the farmers net market gain above the mean (5.6039518).

Table 6: Comparison of net market gain across all possible combinations of market outlets

Market Outlet Choice			
	Mean	**Std. Dev.**	**Frequency**
Cooperatives Only	6.4144289	1.2484056	11
Cooperatives and Wholesalers	5.7608589	0.57583151	14
Cooperatives and Collectors	5.4386399	0.7736183	15
Cooperatives, Wholesalers and Collectors	6.0302382	0.7701476	14
Cooperatives, Wholesalers and Retailers	5.5030667	1.114672	4
Wholesalers Only	5.664407	1.1567654	74
Wholesalers and Collectors	5.5661925	0.46937857	43
Wholesalers a Retailers	4.8046956	1.0610783	18
Wholesalers, Collectors and Retailers	4.8916667	0.50675988	2
Collectors Only	5.6662611	0.99317239	92
Collectors and Retailers	4.5666667	0.25276248	5
Retailers Only	5.3812501	1.8589432	8
Total	5.6039518	1.0178922	300
Test For Equality of 5 Group Means			
	Statistic	**F-value**	**Prob>F**
Wilks' Lambda	0.9046	2.76	0.0020
Pillai's Trace	0.0954	2.76	0.0020
Lawley-Hotelling Trace	0.1054	2.76	0.0020
Roy's Largest Root	0.1054	2.76	0.0020

Source: Own computation, 2020

Determinants of choice of market outlet

In order to identify the major factors that determine choice of market outlet by the small holder potato grower farmers, multivariate probit model was used. Before estimation of the model, test of multicollinearity was carried out to see the extent of association among the independent variables. The test result shows that all the variables have variance inflation factor of less than ten implying that there is no problem of multicollinearity (see Appendix).

The estimation result of multivariate probit model is presented in table 7. The result shows that the model is well fitted as indicated by the Wald test which is with chi2 result of 203.54, implying that the explanatory variables used for the model have significant explanatory powers. The model was also justified by the likelihood ratio test for independence of choices of market outlet, which indicates that there is substantial dependence among the choices (where rho21 = rho31 = rho41 = rho32 = rho42 = rho43 = 0 is rejected because the chi2 is very large enough to accept the alternative hypothesis that there is dependence among market channel choices) so that models like multinomial are irrelevant; rather multivariate model is recommended in such cases.

The correlation result for the choice of market outlets reflects the farmers' behavior. The result shows that there is negative and significant relationship between choice of wholesalers and collectors. Those farmers who provide their produce to collectors are less likely to provide for wholesalers, so does between retailers and collectors. The farmers who provide their produce to retailers do not prefer to provide for collectors. On the other hand, there is significant positive correlation between choice of retailers and wholesalers. The farmers who provide their produce to retailers are also likely to provide for wholesalers.

The result shows that the marginal success probability differs across each type of choice of market outlet. The probability of success to choose cooperatives, wholesalers, collectors and retailers is 20%, 55%, 57%, and 12%, respectively. The implication of this is that collectors and wholesalers are the primary choices of farmers to provide their produce to the market no matter the fact that better price can be gained from retailers and cooperatives. This may be due to perception towards market risks; the market costs facing the farmers while dealing with retailers (Taye *et al*, 2018); and several challenges facing cooperatives. The result also shows that the probability of choosing all these market outlets is 0.009% implying that it is very rare to choose all the market outlets; whereas the probability of not choosing all the four market outlets is 3.4%.

Table 7: Estimation Result of the Multivariate Probit Model

Variables	Coefficients of Choices of Market Outlet			
	Cooperatives Union	Wholesalers	Collectors	Retailers
Age of household head	0.0264938	0.0201472	-0.0119711	0.067628
Sex of household head	-0.7402959	-0.022661	-0.2114063	4.435954
Education of household	-0.329131	-0.4232182**	0.2290613	-0.2236002
Work experience of	-0.0505148	-0.0136793	0.0189482	-0.0852951**
Farm size	-0.5352572	-2.404501***	1.503008***	0.0950034
Total output sold	0.000092	0.0002796***	-0.0000646	-0.0001154*
Proportion of farm income	-0.5797846	-0.2974159	1.26541*	-1.320183
Contractual relation	1.201993***	0.2987025*	-0.1970139	-0.7040626*
Access to market	0.0259653	0.1417206	-0.0152234	-0.040348
Membership to	1.848463***	-0.3572241*	-0.4078068**	-0.7012927**
Access to credit	-0.3499508	-0.5613509	-0.0401524	-3.727556
Access to frequent	0.4640685*	0.1906383	-0.2117796	0.3121114
Mode of payment	-0.110402	-0.3556437***	0.0051167	0.082834
Risk of lack of demand	-0.2187546	-0.0666063	0.0953124	-0.1328789
Family size	0.0695246	-0.078664	0.0724895	0.0137699
Distance to the nearest	-0.1541112***	-0.0605989	0.1000614**	0.1108176**
Woreda	0.4132282	-0.5594895**	0.4390535**	0.418151
Cons	-0.5611185	1.382942	-2.297556	-5.207124

Predicted probabilities0.1981547 0.5506327 0.5790583 0.1215614
Number of obs = 300
Wald chi2(68) = 203.54
Prob > chi2 = 0.0000

rho21 = -.1741417
rho31 = -.1094613
rho41 = 0.0581137
rho32 = -0.7766449***
rho42 = 0.3466622**
rho43 = -0.6512582***

Likelihood ratio test for independence: rho21 = rho31 = rho41 = rho32 = rho42 = rho43 = 0: chi2(6) = 99.6068 Prob > chi2 = 0.0000

Number of simulations (draws) = 5

Joint probability of success = 0.0000914
Joint probability of failure = 0.0337208

Source: Own computation, 2020

Note: ***, **, and * significant at 1%, ** at 5% and * at 10% probability level respectively

Significant factors that determine choice of the market outlet were identified with their level of significances across each choice. These significant factors/variables include: age of household head, education of household head, work experience of household head, farm size, total output, proportion of farm income, contractual relation, membership to cooperatives, access to frequent extension service, mode of payment, distance to the nearest market, and Woreda.

Education of household head: This variable is significant (at 5% level of significance) to forbid farmers not to provide their produce to wholesalers. The result shows that educated household heads rarely provide their produce for wholesalers. This result is also inline to the findings of Mwembe et al., (2021). Their study findings show that the education level of respondents has a negative effect on the choice of farm gate markets. This implies that an increase in the level of education of the respondent reduces the probability of selling at farm gate markets. The findings indicate that educated producers are theoretically aware of the profitability of selling at higher returns market outlets (town markets), being confronted with the higher marketing costs.

Work experience of household head: Work experience is negatively and significantly (at 5% level of significance) related to choosing retailers as point of market outlet. This may be due to the fact that well experienced farmers realize that the market cost for searching and dealing with retailers is very higher as compared to other outlets. In this regard, Taye *et al* (2018) states that the market costs facing the farmers while dealing with retailers is higher even if better price can be gained.

Land size: Those farmers having larger land size prefer collectors to wholesalers as market outlet to provide their produce to the market. The result shows that having larger farm size can significantly (at 5% level of significance) lead the farm household to choose collectors whereas it prohibits the farmers not to choose wholesalers. This result is in line to the findings of Abate *et al*, (2019) which shows that land size has positive and significant relation with the likelihood of choosing town markets than farm gate market. With regard to the possibility of choosing collectors, as land size increases, farmers have the possibility to diversify their crops thereby collectors are the most suitable ones to provide their produce for than wholesalers (who need large quantity of a single type of crop).

Total output: Those farmers with substantial amount of output prefer wholesalers (at 5% significant level) denying their provision for retailers (at 10% level of significance). The study undertaken by Abate *et al*., (2019) also has shown that quantity of produced crop has a positive and significance relationship with the likelihood of choosing wholesalers. The justification behind this is that the farm

households want to sell in large amount than tiny sells when amount of its produce is very larger. Thus, wholesalers are the best options to provide their produce to.
Proportion of farm income: Proportion of farm income is significant variable (at 10% level of significance) to determine the choice of market outlet by the farmers which is pronounced to collectors. The result shows that as proportion of farm income increases, the probability of choosing collectors as market outlet increases. In contrast to this, as shown by Honja *et al*. (2017), access to non-farm income determines the probability of choosing collector outlet negatively. This is due to the fact that farmers who have access to non-farm income are not quick enough to harvest immature mango for temporary cash need because they can derive income needed for the households' basic needs from other activities like trading. In addition to this, farmers who engage in non-farm activities like trading have more knowledge in economic value of selling the crop in formal market and they know as farm gate price diminishes their benefit from selling of crop.

Contractual relation: The farmers who want to sell their produce through contractual relation are likely to choose cooperatives (which is significant at 1%) and wholesalers (which is significant at 10%) whereas it is unlikely to provide their produce to retailers based on contractual arrangement (which is significant at 10%).
Membership to cooperatives: Membership to cooperatives leads the farmers to choose the cooperatives as market outlet (statistically significant at 1%) rather than any choice else. Member farmers of cooperatives are unlikely to provide their produce to wholesalers (statistically significant at 10%), collectors (statistically significant at 5%), and retailers (statistically significant at 5%). This is in line to the finding of Tarekegn et al. (2017).

Access to frequent extension service: If the farmers have frequent access to extension service, they probably choose cooperatives as market outlet (which is statistically significant at 10%). This result is in line to the findings of Tarekegn et al. (2017) which indicates that frequency of extension contact has a positive and significant influence on cooperative outlet choice decision. Extension services increase the ability of farmers to acquire important market information as well as enable the farmers to improve production methods, hence leading to more output which in turn increases producers' ability to choose the best market outlet for their product. Thus, households who were visited more by extension agents were more likely to deliver the crop via cooperative outlets.

Mode of payment: For mode of payment that tends to be not on cash, the farmers are not likely to provide their produce to wholesalers (which is statistically

significant at 1%). This may be due to the fact that wholesalers buy the products from the farmers fully on cash.

Distance to the nearest market: As the distance to the nearest market is getting higher, the possibility of choosing cooperatives as market outlet reduces (which is statistically significant at 1%). This can be an indication for the small outreach of cooperatives specially for remote areas. On the other hand, the possibility of provision of the produce is higher for collectors and retailers, at 1% and 5% level of significance. In consultation with agricultural experts in the area, it was clarified that collectors and retailers usually go to far remote areas to get the produce from the farmers.

Woreda/district: This is a Woreda dummy variable (for Haramaya and Kombolcha) which is significant variable to determine the choice of farmers for market outlet (at 5% level of significance for both wholesalers and collectors). The result shows that farmers in Haramaya possibly prefer collectors to wholesalers. They choose collectors because the main market for potato, around which many wholesalers are found, is Kombolcha city. Hence, farmers of Haramaya possibly provide their produce to collectors which is to be sent to Kombolcha's wholesalers and buyers such as exporters.

Concluding Remarks

In this study, it was identified that there are four major market outlets in the region for potato growers. These include: cooperatives, wholesalers, collectors and retailers. Hence, given that multiple choices can be made by the farm households, there are 15 possible combinations of choices for the farmers. In fact, three of these combinations do not actually exist based on the response of the sample farm households.

The result of the study reveals that most of the potato farm households use collectors only, wholesalers only or both as outlet for marketing for their produce. Unfortunately, very few potato farm households were able to sale their produce via agricultural cooperatives due to the cooperatives' limited operational capacity. However, the study shows that using cooperatives as market outlet can bring about better market gain as compared to the rest alternatives of market outlet. Hence, it is recommended that it would be better to improve the operational capacity of the agricultural cooperatives. In this regard, there should be strict follow-up on the cooperatives' performance as well as active participation of member farmers is inevitable.

The combination of using cooperatives, wholesalers and collectors was also found to provide relatively higher market gain next to using only cooperatives as market outlet. This implies that it is also a good option for the farm households to use multiple market channel alternatives, in case they are not able to provide their produce only to cooperatives.

Results of the multi-variate probit econometric model indicate that choices of the farm households are interdependent. There is significant trade-off of choice between collectors and wholesalers, so does between retailers and collectors. Given such trade-offs, agricultural extension agents should provide better market information that guide farmers to which market channel they provide their crops. There should also be clear framework of coordination in production and marketing activities.

On the other hand, there is significant co-existence of choice between wholesalers and retailers. The model result also shows that collectors and wholesalers are the primary choices of the potato farmers to provide their produce to the market no matter the fact that better price can be gained from retailers and cooperatives. Hence, there should be regulatory organs that can limit the market margin of these market participants in favor of the farm households.

With regard to determinants of choice of market outlet by the potato farm households, results of the multi-variate probit regression reveals that 10 of the expected variables were found to be the significant factors to determine the choice of market outlet by the potato growers. Membership to cooperatives (being against wholesalers, collectors and retailers) and contractual relation intend to lead the farmers sell their produce via cooperatives. Hence, on the top of improving the operational capacity of the cooperatives, training on marketing contractual arrangements is crucial as contractual agreements may matter to secure better market gain.

However, distance to the nearest market reduces the possibility of using cooperatives as market outlet for the farmers. The implication of this is that the outreach of cooperatives likely to be limited to areas around market centers or cities. Thus, there should also be due attention to improve the outreach capacity of agricultural cooperatives to far remote areas.

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Appendix

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. vif

    Variable |       VIF       1/VIF
-------------+----------------------
     workexp |      4.35    0.229882
        ageh |      4.05    0.246907
      woreda |      1.77    0.564465
modeofpaym~t |      1.48    0.674295
  totprodpot |      1.48    0.676859
  riskdemand |      1.46    0.684355
    distmark |      1.46    0.685041
 contractall |      1.43    0.698619
 totalfamily |      1.41    0.710677
  membercoop |      1.27    0.790347
accessmark~o |      1.23    0.812088
       educh |      1.23    0.812706
    farmsize |      1.20    0.833370
accessexte~n |      1.19    0.839766
 propfarminc |      1.17    0.852350
accesscredit |      1.13    0.888006
        sexh |      1.09    0.917627
-------------+----------------------
    Mean VIF |      1.67
```