Innovations

The relationship between farm and non-farm activities of smallholder farmers; Evidence from Western Ethiopia

Mr. Wakuma Dufera, Dr. Amsalu Bedemo & Dr. Temesgen Kebede

[1.]Ph.D. candidate at Wollega university in Development Economics, Department of Agricultural Economics, College of Natural Resource Management, Salale University, Ethiopia
2. Associate Professor of Economics, School of Policy Studies, Ethiopian Civil Service University, Ethiopia
[3]Assistance professor of Economics, Department of economics, College of Business and Economics, Haramaya University, Ethiopia
*Corresponding author: **Mr. Wakuma Dufera**

Abstract
Farm and non-farm sectors reinforce each other to support living in a rural area, that is, just as a non-farm activity contributes to farm growth; agricultural activity also contributes to the development of the non-agricultural sector. The objective of the study was to identify the link between farm and non-farm activities. In this study, a multi-stage sampling method was used to select 383 sample respondents in the study area. The data was analyzed using the SUR bivariate model. As a result, bivariate SUR econometric results showed that variables such as land size, age, credit, distance from market, education, training, livestock(TLU), and membership of iqub frequently determined both sectors (farm and non-farm). The study recommended that agricultural development strategies issued by the government should include non-agricultural activities as well.

Keywords*: 1. non-farm,2. Farm,3. Nexus,4.rural households,5. SUR model*

1. Background of the study

Farm and non-farm activities are interdependent activities in which the life of the major Ethiopian rural households is relayed. Participation in non-farm activities includes a wide range of economic activities in rural areas(Musa and Hiwot, 2017). Non-farm employment has the potential to play a key role in the holistic and inclusive development of Ethiopia's rural areas by increasing farm production (Apelike et al., 2021). For several reasons, such as lack of adequate financing, the presence of well-functioning rural non-farms can act as a complementing force in balancing agricultural income swings by reducing the vulnerability of rural households (Babatunde and Qaim,(2010). Awoke,(2019) in his study of income diversification argues that "*non-farm participation is a central topic in the improvement of farm production in rural Ethiopia, given its role in reducing poverty through income generation and, more generally, for ensuring rural household's food security*".

Several studies have also discovered a link between farm and non-farm activity(Chand et al., 2009; Consol and Nelson, 2014; Kassie et al., 2017; Kaiyu et al, 2021; Iqbal et al., 2017). The growing importance of non-farm work to farm households' economic well-being has spurred a lot of discussion among scholars on the role of non-farm employment in food security, agricultural productivity, and household income. The link between farm and non-farm activity, however, is a point of contention. The first point of contention is that non-farm work is predicted to reduce on-farm labor availability and allocation, thereby limiting agricultural productivity (Musana et al., 2012; Neglo et al.,2021; EEA, 2021). Non-farm labor, on the other hand, allows farm households to stabilize household income and reduce vulnerability and uncertainty connected with agricultural production (Kassie et al., 2017; Anteneh and Gazuma,(2019); Beyene, 2019). According to the study by Gideon et al.,(2020); Pandey et al.,(2012); Tamrat et.al, (2020), participation in non-farm work has two effects on agricultural productivity: a negative lost-labor effect and a positive income or liquidity-relaxing effect.

When a household loses farm labor to non-farm activities, the negative lost-labor effect occurs, but the positive income effect happens when the household gets revenue from non-farm activities that it can invest in farming (Zewdu and Woldeyohannis, 2021). Non-farm work's negative impact on farm revenue, on the other hand, will be determined by which of the two effects is stronger. For example, a poor farm household's labor input allocation could be shifted from rain-dependent livelihood activities to alternative environmentally friendly off-farm and non-farm income-generating activities like commerce and rural small-scale manufacturing (Ganamo and Astatike, 2019).

Considering the issue of these shortcomings, this study focused on the relationship between farm and non-farm employment in the western part of the country in general and Horo Guduru Wollega zone in particular. Horo Guduru Wollega zone like most of the rural villages in Ethiopia depends on agriculture for its livelihood. Their source of income is agriculture, but many farmers cannot support themselves through agriculture alone. Rural households support their families with additional income obtained from non-farm activity. As a result, the link between farm and non-farm employment requires research and explanation. So, the objective of this study was to assess the relationship between farm and non-farm activities in the study area.
Participating in non-farm activities could increase overall cash income. If the income from non-farm activities is used to finance farm input purchases or long-term capital investments, it can be an important source of cash that is potentially used to improve farm productivity Adeoye et al., (2019); Musana et al.,(2012). Several studies show a positive effect of non-farm income on the use of purchased inputs, for instance: Kaiyu et al,(2021) from South Africa; Kassie et al.,(2017) from Ethiopia; Pandey et al.,(012)from South Asia; and (Amare et al., 2017; Anteneh and Gazuma,2019; Apelike et al., 2021) from Ethiopia.

In their study of farm and non-farm linkages, Möllers et al .,(2011) stated that "the resources must flow from the agricultural sector to the non-agricultural sector. This means agriculture provides labor, capital, and foreign exchange for the expansion of the non-farm sector food for those engaged in the non-farm sector as well as the raw material too". Musana et al.,(2012) in their study of the role of the development of enterprise also stated the link between farm and non-farm as, "*rural farms act as a source for supplying labor for the expansion of urban industry*".
In this case, the expansion of rural non-farm activity is enabled by the development of the industry. Tamrat et. al,(2020) also stated that *non-farm income might serve as a good risk management tool*. Farm households also undertake non-farm activities as a way of avoiding the risks of agriculture (Oladimej et al., 2015).According to the study by Oluyemisi,(2018);
"Non-farm activity has a great role in providing households with income security and liquidity to invest in new production activities or technologies, especially under the imperfection of the credit market"

Hence, in a most rural areas of Ethiopia, farm households are highly reliant on non-farm income, and that can have good implications to be considered by agricultural research and extension. Reinvestment of non-farm profit back into farm production can be expected to improve farm productivity and household food security(Yenesew et al, 2015). However, it is unclear how much income from non-farm activities is reinvested back into agricultural production. It is widely assumed that surplus income generated by non-farm activities can provide high security to farmers, allowing for greater farm innovation(Gideon et.al, 2020). All of this research shows that non-agricultural work is linked to farm development and is a major contributor to the growth and development of agricultural production.

3. Methods of Data analysis

1.1 Description of the study area

Horo Guduru Wollega zone is one of the eighteen administrative zones in Oromiya National Regional State, Ethiopia. The capital of the administrative zone is-Shambu, which is located at 310 km west of Addis Ababa, the capital city. It has nine administrative districts and one town municipality. The 2018 population projection of the Central Statistical Agency (CSA) of Ethiopia shows that the zone has a total population of 511,737, out of which 50.1 percent are male and 49.9 percent are female. Rural areas are home to approximately 89 percent of the zone's population(CSA, 2018).

The total area of the Horo Guduru Wollega zone is 712,766.22 hectares. In terms of agroecology, the highland comprises 37.9 percent, the mid-highland comprises 54.75 percent, and the lowland comprises 7.86 percent (HGWOARD, 2022). Its rainy season occurs between May and September, and the dry season lasts from October to April. The rainy season in the area fluctuates from year to year, but it covers about five months. Clay and sandy soils are the major soil types of the zone(CSA, 2013).

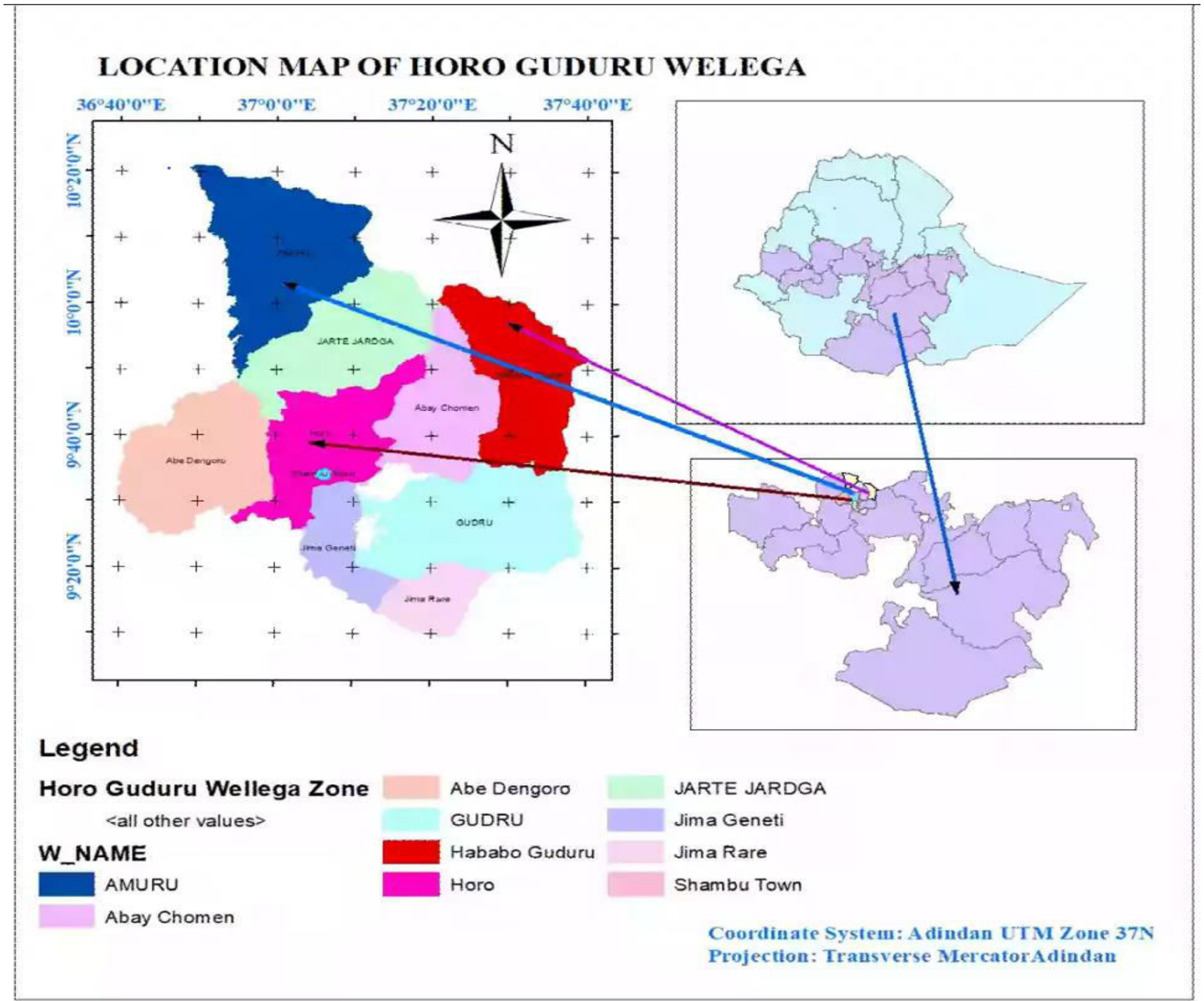

Figure 1: Map of the study area
Source: GIS department, 2022

3.2 Research design

To collect information for this study, a cross-sectional research design was selected for this research in a way that the researcher can describe the current and up-to-date information about consumption expenditure, household characteristics, farm/non-farm linkages, and the determinants of non-farm from primary data, rather than secondary data, through direct interviews with stakeholders. This research design includes both qualitative and quantitative data, which includes the 2021/22 production year, and was applied to this research work.

3.3 Sources of data and methods of data collection

This study used the data collected from primary sources. To supplement the primary data, secondary data was collected from concerned district offices (like Woreda Agricultural Office, Zonal Agricultural Office, and Central Statistical Authority) and published and unpublished sources. The data collection for this study was qualitative. Primary data contains detailed information on households' characteristics, socioeconomic characteristics, demographic characteristics, farm characteristics, agricultural inputs utilization, the output produced, and production problems encountered. The data was collected from 383 selected sample farm households using structured and semi-structured questionnaires filled by trained data collectors who are good at the local language.

3.4 Sample size determination and sampling procedure

According to the 2022 Financial and Economic Cooperation Planning and Programming Department report of the study area, there were 106,038 household heads in the nine districts, accounting for 20% of the district's population. That is, the total number of household heads represented 20% of the zone's population of 511,738. The population variability of the data was p=0.2 and q=1-p=0.8. According to the sample determination formula employed by the researcher to decide the sample presented in equation 3.1, it was discovered that increasing the sample size was necessary to improve the data quality. Hence, the most commonly used formula for a questionnaire analysis was sample size determination when the population is large and finite according to Kothari,(2004), a representative sample is needed to analyze proportion. The formula was:

$$n = \frac{Z^2 pqN}{\varepsilon^2 (N-1) + Z^2 pqN} \qquad [1]$$

Where, n= the required numbers of sample

z =the value of the desired confidence level or confidence interval (95%=1.96),

The maximum variability among the population p= (0.5), q = 0.5 which is equal to (1-p)

and e=±5 % margin of error/precision by looking at the expected criteria.

When we apply the formula

$$n = \frac{(1.96)^2 0.5(0.5)106{,}038}{(0.05)^2(106{,}037)+(1.96)^2(0.5)(0.5)} = \frac{101{,}838.8952}{266.0529} = 382.7 \approx 383$$

Therefore, the required sample sizes of this study were 383 households. But, the question is how can these individuals be selected? These sample sizes allotted to the three woredas were based on a proportionate sampling method. Though with this method each woreda was fairly represented, a proportional allocation of the sample was made based on the size of households in each woreda. This means the sample size was allotted to three woredas (districts) using proportionate stratified sampling formula. Through this formula, each woreda was fairly represented as follows:

1. A sample size of Horo Woreda = $\frac{5703x383}{20{,}318} = 108$ household heads
2. A sample size of Hababo Guduru Woreda $\frac{6{,}073x383}{20{,}318} = 127$ household heads
3. A sample size of Amuru Woreda =$\frac{6{,}436x383}{20{,}318} = 149$ household heads

Table 1: Distribution of total and sample households in the sample kebeles

	Sample selected woreda	Total rural household heads			Sample household heads		
		Male	Female	Total	Male	Female	Total
	Horo district	4,903	800	5,703	93	15	108
	Hababo Guduru district	6,073	655	6,728	115	12	127
	Amuru district	6,436	1450	7,887	121	27	148
	Total sample	17,412	2,905	20,318	329	54	383

Source: own computation from CSA,(2018b)

Thus, information from these 383 households was collected by using a multistage sampling technique. In the first stage, Horo Guduru Wollega zone was chosen from the Western Oromia region purposively because the area is characterized by highly populated area and too high landlessness when relatively compared to other western areas of the country CSA (2018). In the second stage, three districts were selected by systematic sampling because all districts in Horo Guduru Wollega zone have almost similar socio-economic and cultural characteristics. Thus, the woreda was selected systematically at an interval of four from the list of nine districts by using the third as a reference point for starting. By selecting the third woreda as the first part of the sample from the list of all woreda[1], Horo, Hababo Guduru, and Amuru were selected. There are 11, 12, and 21 rural kebele in Horo, Hababo Guduru, and Amuru districts, respectively, and the total kebele in the three districts are 44. It is possible to allocate the sample households to all 44 kebele. But due to time and budget constraints and for the simplicity of the data, 16 kebele were determined from all 44 kebele by convenience sampling based on Kothari (2004).

To reduce the bias of the convenience sampling problem, the selected kebele were allocated to each woreda proportionately: 4 kebele from Horo district, 4 kebele from Hababo Guduru district, and 8 kebele from Amuru district. In the third stage, sample households were allocated to each selected kebele proportionately based on the total household number in each sampled kebele. In the fourth stage, simple random sampling was used to select a total of sample households from the list of the population in each kebele by using a random number table because all households have an equal chance of being selected. Therefore, this study was based on the use of both probability and non-probability techniques of sampling. The proportionate sample in each kebele was:

$$n_{ki} = \frac{N_{ki}}{\sum N_k} X \; n_k \qquad [2]$$

Where i=1,2,3....list of each kebele and k=represents name of each kebele

n_{ki} =sample in each kebele

N_{ki} =total household head number in each kebele

$\sum Nk$ =Total household head number in given woreda of kebele (total population)

n_k=total sample of household heads in a given district means 108,127 and 148 samples for Horo ,Hababo Guduru, and Amuru districts respectively.

3.5 Methods of data analysis

Econometric models, more specifically for the relationship between farm and non-farm sector participation was mostly described by using the concept of the nexus between farm and non-farm participation. In this section, the proxies to farm/non-farm linkage dependent variables are two: non-farm participation (Y = 1 for participating and 0 = otherwise) and farm activity participation (Y = 1 for participating in farm activity and 0 = otherwise). To analyze this relationship, a SUR bivariate model was used.

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[1] A woreda;-is a subordinate political subdivision of a region's zones that is analogous to the term "district" elsewhere.

3.6 Econometric model

In analyzing the link between farm and non-farm participation, for example, in a set of individual linear multiple regression equations, each equation may explain some economic phenomenon. One approach to handling such a set of equations was to consider the setup of a simultaneous equations model in which one or more of the explanatory variables in one or more equations are themselves the dependent (endogenous) variables associated with another equation in the full system. On the other hand, suppose that none of the variables in the system are simultaneously both explanatory and dependent.

The relationship between farm participation and rural household participation was examined by using a seemingly unrelated bivariate probit model. Non-farm participation (1 if the household head participates, 0 otherwise) and agriculture participation are both dichotomous variables. Because there is just one binary dependent variable (Y) in the traditional probit model, only one latent variable(Y*) is used. The bivariate probit model, on the other hand, has two binary dependent variables, Y_1 and Y_2.

Y_1* and Y_2* are the two latent variables. Each observable variable is assumed to have a value of 1 if its underlying continuous latent variable has a positive value, otherwise a value of zero. Assume that non-farm (Y_1) and farm (Y_2) participation will be endogenous variables, whereas socioeconomic, demographic, and institutional aspects will be exogenous variables. Then the equation of a skewed unrelated bivariate probit regression model can be specified was specified as:

$$Y_{it} = \begin{Bmatrix} 1\ if\ Y_{it}^{*} > 0 \\ 0 = otherwise \end{Bmatrix} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. [3.15]$$

$$Y_{2t} = \begin{Bmatrix} 1\ if\ Y_{2t}^{*} > 0 \\ 0 = otherwise \end{Bmatrix}$$

With

$$Y_{1_t} = X_1\beta_1 + e_1$$

$$Y_{2_t} = X_2\beta_2 + e_2$$

And where Y_{1t} and Y_{2t} are mutually dependent or endogenous and Y_1 and Y_2 are binary coded participation in farm activity and X's are exogenous variables, ε_1 and ε_2 are the stochastic disturbance terms. Fitting the bivariate probit model involves estimating the value of $\beta 1, \beta 2$

and Y_i. To do so; the likelihood of the model is maximized as:

$$L(Y_1, Y_2) = [p(Y_1 = 1, Y_2 = 1 / Y_1, Y_2)^{Y_1 Y_2}\, p(Y_1 = 0, Y_2 = 1 / \beta_1, \beta_2)^{(1-Y_1)Y_2}\, p(Y_1 = 0, Y_2 = 0 / Y_1, Y_2)^{(1-Y_1)(1-Y_2)}$$
$$p(Y_1 = 1, Y_2 = 0 / Y_1(1 - Y_2)\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots[4]$$

The coefficients of these parameters must be transformed to yield estimates of the marginal effects. The bivariate probit model is based on whether or not p is significant. If a Wald test shows that p is significant, then both farm and non-farm participation employments are endogenous. If p is not significant, then no endogenous bias is present and both equations can be estimated separately as binary probit.

4. Econometric Results of a Seemingly Unrelated (SUR) Bivariate Probit Model

A substantial share of agricultural and non-farm products is vital to expanding rural family consumption in western Ethiopia. Non-farming activities can be an important part of an individual consumption improvement approach. However, its significance in terms of raising rural household consumption is based on several interrelated elements, as well as an assessment of farm activity and reactions to determine if the non-farm will be effective or not.

Appropriate non-farm participation might be viewed as a need for selecting an effective consumption-increasing approach. According to this study result, a farmer who does not participate in non-farm activities is unable to successfully raise consumption. Non-farm participation might be low due to farm participation or high due to farm participation. Many determinants affect farming activities in the research area, including a lack of seeds, pesticides, fertilizer, and technical assistance to household heads, with numerous scenarios in between. Non-farm can also be signed by individuals or groups of heads from both farms and non-farms. This strongly shows that engagement in farm and non-farm activities, rather than reliance on specific farm goods, is an important component of improving rural household living conditions.

Table 1 shows the results of the full information maximum likelihood estimation of a seemingly unrelated bivariate probit model. The null hypothesis of zero connection between the disturbance term of non-farm participation and farm participation is rejected at 5% significance level. This means that using an unrelated bivariate model is permissible.

The Tetrachoric correlation also demonstrates that non-farm and farm participation are interconnected and positively associated at the 1% significance level. The implication is that variables influencing non-farm activity also influence non-farm participation, meaning that the two (farm and non-farm) are interconnected. This strongly suggests that non-farm participation, rather than reliance on specific farm products, is a significant component in consumption to better rural household living. At the 1% level of significance, Pearson's correlation coefficient is also 0.4710. As a result, there is a positive and significant association between households' farming and their decision to participate in non-farming activities. A seemingly unrelated bivariate probit model fits the data well in general. The Wald chi-square test significantly rejects the null hypothesis, and the model properly predicted the observations. Robust standard errors were supplied to address the heteroscedasticity issue. Table 1 shows the results of an unrelated bivariate probit analysis, which revealed that participation in training, availability of credit, distance to neighboring roads, membership in iqub, and landholding size are among the relevant variables influencing non-farming participation. The interpretations of the results for each variable are given below in Table 1.

Table 1:-Parameter estimates of seemingly unrelated bivariate probit regression

Variables	Coefficient	Robust Std. Error	Z-value
Participation in farm activity			
Age^2	-.0126002***	.0021354	-5.90
Education	.0158087**	.0001122	3.84
Membership of iqub	.0779253**	.021024	8.71
Total livestock	-.0087583***	.0030633	-2.89
Land size	.026945***	.0092132	2.92
Household health status	.3237226***	.0268367	12.06
Access to train	.0933027***	.0249504	3.74

Distance from market	-.0259301***	.0030844	-8.41
Membership of idir	-.0151024	.0049263	-1.15
Number of household dependent	-.0336533**	.292147	3.07
Gender	-.0718509***	.0218929	-3.28
Access to credit	.252207***	.0254481	8.06
Number of oxen	.0417744***	.0117372	3.16
Const.	.9515775***	.1052157	9.04
Participation in non-farm activity			
Age	-.0177547***	.0029765	-5.97
Education	.0109661**	.0048578	2.26
Membership of iqub	.0872551**	.0297303	2.93
Total livestock	-.0103008**	.0043274	-2.38
Land size	.03442***	.0131231	2.62
Household health status	.2780152***	.0398279	6.98
Access to train	.1203023***	.0347655	3.46
Marital status	.0461026*	.0344938	1.34
Distance from market	-.0524941***	.0042722	-7.61
Household saving participation	.0328844	.243919	1.35
Membership of idir	-.322275	.0421717	0.77
Number of household dependent	-.0217637***	.0070547	-3.65
Gender	-.1208713***	.0337287	-3.58
Access to credit	.1313117***	.1357108	3.68
Own mobile phone	-.07204051*	.0265074	-2.72
Cons.	1.369982***	.1524885	8.98
/anthro	14.32674	457.1472	2.68
Rho	0.32	0.058	
Wald test of rho=0: chi2(1) = 17.3863**			
Wald chi2(19) =264.90*** Log pseudo-likelihood = -62.68 Tetrachoric rho = 0.7898*** Std error = 0.0481 Test of Ho: participation in farm and non-farm activity are independent Pearson's correlation coefficient = 0.4710*** Joint probability of success = 0.118 and Joint probability of failure = 0.214			

Note: ***, **,*, represent level of significance at 1%, 5% and 10%, respectively

Source: Own Computation Result Based on Survey Data (2022)

In general, the data was well fitted by a bivariate probit model that appears to be unrelated. The null hypothesis was strongly refuted by the Wald chi-square test, and the model correctly anticipated the observations. To overcome the heteroscedasticity issue, robust standard errors were provided. Table 1 displays the findings of a bivariate probit analysis, which at first appearance seems unconnected. This analysis showed that among the key characteristics impacting participation in farm activity were age, education, membership in iqub, distance to the nearest market, total livestock, and landholding size. Participation in training, Idir membership, the number of oxen, and access to credit were a few significant variables affecting farm activities. Reho=0.32 which shows the correlation between the error terms of the equations is positive, which is statistically significant. The finding implies that there was a positive relationship between household farm participation and non-farm participation decision. If the household is more likely to participate in non-farm, then the probability of farm participation is high. This finding confirms the positive relationship between non-farm and farm. In addition, the SUR result interpretation is that error terms of each equation are related to show that both have common unobserved factors which influence the dependent variables of the equations. The following are interpretations of the results for each variable;

Participation in training: The variable access to training is found to positively and significantly affect both farm and non-farm participation at 9 and 12 percent, respectively. The interpretation of the result is that training commonly affects positively both farm and non-farm activity.

Age: - At a 1% statistically significant level, this variable has a detrimental impact on both farms and non-farms. This suggests that age has a favorable effect on both sectors whereas age 2 has a negative effect on both farm and non-farm. The interpretation is that the head of the household can support his family in his youth by doing all of the productive work in agriculture and non-agriculture, but as he ages, he has less strength to take on all of the obstacles in agriculture and non-agriculture. However, as the head of the family ages, their interest in agriculture and non-agriculture declines.

Education: The variable has a statistically significant positive effect on farm and non-farm participation at 5% and 1%, respectively. Education is critical for quickly adapting to technology. The interpretation of the study's findings indicates that education is also required for a person to conduct agricultural extension, acquire business training rapidly, and benefit from business results.

Distance to market/road: This variable has a negative and statistically significant effect on both farm and non-farm participation at 2.5 percent and 5.2 percent respectively. This is because farmers who are far from the road are less attracted to farm and non-farm markets as it is costly for transportation. Moreover, the farther the farmer is away from the main road, the lesser his/her profit margin as he/she pays more money for transportation and intermediaries. Hence, both farm and non-farm participation depends on infrastructural development. This result validates the findings of Zewdu and Woldeyohannis,(2021) which is based on a study conducted in India.

Access to credit: The fact that access to finance has a positive and statistically significant effect suggests that this variable would improve the likelihood of engagement in both agricultural and non-farm activity. Access to credit, for example, may play a key influence in the adoption of contemporary technologies in the farming and non-farming sectors. Credit can be used as both working capital for the purchase of agricultural inputs and as start-up capital for non-farm activities. The finding is consistent with reports made by Asfaw,(2022)who claim that farmers' access to credit is one potential motive for participating in non-farming. This makes sense because farmers with limited access to financing may be especially exposed to market volatility and may have financial difficulties in non-farm operations. Non-farm activities also give farmers a means of getting cash and/or in-kind loans, providing another incentive for credit-constrained farmers to participate in farming activities.

L**andholding size:-**land size is considered a major asset in the rural area of this study. A person with large amounts of land is considered to have a large security for his family. Thus, people with large tracts of land have a greater opportunity to contract their land for large-scale agricultural production and even to start non-farms. The results show that land size is positively and statistically significant at 1 percent for both farm and non-farm participation. The implication is that land size positively affects both farms and non-farm.

Household health status:-Table 1 depicts that the health of the household head has a significant impact on engagement in agriculture and non-agriculture. In this study, the variable had a positive and statistically significant effect on both farms and non-farms at a 1% significance level. An interpretation is that a healthy family head can work day and night without any restrictions in his chosen agricultural or non-agricultural occupation to support his family. This means that if the health of the head of the household is good, the decision on whether to farm or not is limited only by the choice of the head of the household. The head of the family, who is suffering from health problems, spends his time in bed in addition to spending money on hospitals to ensure his health.

The number of family dependents: According to the research area, family dependents are children under the age of five, the elderly, and bedridden patients suffering from various ailments who require particular care. As a result, these dependents rely on those who can produce for their families. This variable has a statistically significant negative effect on farm and non-farm participation at 5% and 10%, respectively. This means that as the number of family dependents grows, there will be less decision-making on the farm and non-farm issues. Since the head of the home spends the majority of his time caring for these dependents, their participation in agricultural and non-agricultural activities is lower.

Membership to *iqub*; Membership in iqub is considered statistically significant at a 10% level of probability, supporting the a priori hypothesis. One likely interpretation is that farmers typically keep money in the form of iqub to meet financial risk. Furthermore, as a social network, iqub plays a role in conveying reliable information, promoting the exchange of knowledge on the possible consequences of unpredictable weather hazards, and facilitating the dissemination of risk mitigation measures. In summary, the results obtained in this study provide valuable insights for both agricultural and non-agricultural participants. More precisely, the findings could help mitigate financial crises related to agricultural production and participation in non-agricultural activities. The findings also have implications for motivating the provision of non-farm and agricultural inputs that improve household finance.

Gender:-this variable affects agriculture and non-agriculture negatively at a statistically significant level of 1 percent. Women heads spend most of their time doing housework and raising children. On the other hand, women's heads live under male domination and do not have the freedom to make their own decisions. The interpretation of these results is that being female head reduces decision-making in agriculture and non-agriculture.

The number of an ox; **-** This variable has a positive effect on agricultural participation with a statistically significant proportion of 1%. Having a pair or more than a pair of oxen helps household heads to do agricultural work such as plowing and threshing to facilitate agricultural work. The interpretation of the results is that the availability of steering resources in agriculture plays an important role among the inputs that motivate crop producers. On the other hand, owning an ox is one of the best ways to increase agricultural participation as it is a crucial factor in agricultural production.

Marital status; **-** At 10%, marital status has a statistically significant positive effect on non-farm participation. Indeed, it is difficult for an unmarried head of household in a rural area to exercise both agricultural and non-agricultural activities. This means that married heads of households are more likely to participate in non-agricultural activities because they have more time to do both. In contrast, unmarried people are less likely to engage in non-agricultural activities because they have less time to engage in agricultural and non-agricultural activities.

Membership in Idir; - is a social tool used by the community to come together voluntarily to create rules and help each other through difficult and happy times. This variable is not statistically significant even though it negatively affects agricultural and nonagricultural holdings. It is understood that adherence to the Idir of this interpretation is not required as it is a social matter for people to work together on days of need or good fortune and plays no role in empowering the decision to engage in farming or non-farming to participate.

Own Mobile phone: Today is the time for information, so it is important to have a mobile phone in rural and urban areas. Mobile ownership has a negative impact on non-agricultural participation, and the result is statistically significant at a 10 percent level of significance. This suggests that holding a mobile phone has a negative impact on non-farm participation. The interpretation of this is that according to the practical situation in the study area, the continuing problem is that due to power outages and network failures, mobile phone owners cannot charge their mobile phones, and their cell phones are blocked for a long time.

5. Conclusion and recommendation

Non-agricultural activities help accelerate agricultural activities, and income from agriculture supports non-agricultural activities. Agricultural activity is important for rural households and for improving the consumption of rural livestock. Although the development of non-agricultural activities in rural areas is weak, they have played an important role in improving agricultural activities and increasing the livelihoods of rural households.

However, many factors generally hinder the development of agricultural and non-agricultural activities. Some of the determinants of agricultural development are lack of financial loans, lack of timely deliveries of fertilizers and selected seeds by trade unions, lack of ox farms, and lack of land for agriculture. In the field of non-farm development, there are problems such as lack of debt, lack of education on non-farm issues, gender inequality, and inadequate formal education for adults. The results of the study show that factors that influence non-agricultural activities also influence agricultural activities. Based on the above, the recommendations were that the head of a rural household's focus is mostly on agriculture, and non-agriculture is seen as a secondary job, weakening their decision to do non-farm work. So, the relevant authorities should provide awareness of the non-farm benefits of the head of household, in the form of training, encourage borrowers by making a discount rate for the householder to get the loan and infrastructure, especially roads connecting urban and rural areas, needs to be addressed to improve the livelihoods of rural households.

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*Corresponding email;**wakuma.dufera2009@gmail.com***