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Application of Double Hurdle Model in the Analysis of Determinants of Income Diversification and Its Intensity: Evidence from Gida Ayana District

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Abstract

Diversification of income sources, assets, and occupations is often common practice for individuals or households in different parts of the world, but for different reasons. Although less productive, compared to modern sectors, the contributions of rural non-farm works to economic growth, rural employment, and poverty reduction. This study attempted to identify potential factors influencing non-farm income diversification in Gida Ayana district based on the data obtained from 196 rural households. Descriptive results depicted that 34.2% of the sampled households were engaged in non-farm works that are performed as a complement to agriculture part-time or during the agricultural off-seasons. An econometric result from the first hurdle model revealed that households' participation in non-farm work is positively and significantly influenced by education of household head, number of oxen, access to credit and access to market information while negatively and significantly influenced by the use of fertilizer. Similarly, the second hurdle model result showed that the amount of income from the non-farm sector is positively and significantly influenced by the number of oxen and access to market information while negatively and significantly affected by distance to the nearest market and use of fertilizer. Based on the result, households in the study area are recommended to diversify the source of their income for their family need in addition to farm income since the proportion of non-farm income remains low. The effort of the local agricultural sector and development agents are also required to expand rural infrastructure.

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Introduction

Diversification can be defined as the maintenance and continuous alteration of a highly varied range of activities and occupations to minimize household income variability, reduce the adverse impacts of seasonality, and provide employment or additional income (Haggblade *et al.,* 2010). Agriculture provides investment opportunities for the private sector and primarily derives related agricultural industries and rural non-farm economies. Agricultural production is important for food security as it is a source of income for the majority of the rural poor (World Bank, 2008). In regions where agriculture has grown robustly, the rural non-farm economy has also typically enjoyed rapid growth. In contrast, regions with poor agricultural potential have seen more limited prospects for rural non-farm growth, except in places where other important rural tradables, such as mining, logging, and trade, offer an alternative economic platform for sustaining regional growth. The rural non-farm economy includes a highly heterogenous collection of trading, agro-processing, manufacturing, commercial, and service activities.The scale of individual rural non-farm businesses likewise varies enormously. Often highly seasonal, rural non-farm activity fluctuates with the availability of agricultural raw materials and is in rhythm with household labor and financial flows between farm and non-farm works (IFPRI, 2009). The Ethiopian economy still remains dominated by the agricultural sector and the majority of the population still makes a living in this sector. However, pull and push factors derive rural households from diversifying their income sources. Rural population growth, farm fragmentation and decline of agricultural productivity were among the pull factors to engage in non-farm activities. Pull factors such as urban and rural demand can lead to non-farm activities that enhance the households' economic standing (Prowse, 2015).Many smallholder farm households complement their farm income with income from non-farm sources. This strategy has several advantages, especially for poorer households. Their agricultural resources are often too limited to allow efficient use of all household labor, and non-farm activities can offer analternative remunerative allocation, especially during the lean season. Moreover, income from agriculture is subject to high risk due to climatic factors, price fluctuations, pests and diseases. Earnings from non-farm employment may help to buffer the resulting income fluctuations and improve household security (Jean and Peter, 1995).

In regard specifically to rural Ethiopia, households have been found to diversify their income sources due to both push and pull factors and previous studies suggest that the determinants of income diversification in rural Ethiopia vary according to wealth status (Browse, 2015). Adugna (2009) used Ethiopian Rural Household Survey data collected from 1500 rural households in 1994 and 1997 to examine the determinants of income diversification in rural Ethiopia. He argued that families with a high dependency ratio, female household heads, high livestock value, and poor quality of land participated less in off-farm activities even if the data used is old. Browse (2015) examined determinants of non-farm income diversification in rural Ethiopia for a four-wave panel of 1240 households from the Ethiopian Rural Household Survey over the period 1994–2009. The results suggested that among the variables that determine non-farm diversification, consumption per capita and livestock holdings belong to pull factors and reflect a strategy by wealthier households. Although country-level data was used, there might be a doubt on the representativeness and reliability of such secondary data during adoption.

Tshabalala and Sidique (2020) investigated determinants of non-farm enterprise diversification in rural Ethiopia using Ethiopian Rural Socioeconomic Survey data from 2011 to 2016. The results from the panel double hurdle model for non-farm enterprise diversification show that the decision to participate is determined by the age of the household head, household size, distance to markets, access to credit and social capital. In contrast, the income level is affected by the age and education level of the household head, household size, distance to market and access to credit. Getachew (2012) examined the effect of poverty on participation and intensity of rural non-farm sector in the Amhara region of Ethiopia using pooled data of 366 random rural households from the last two rounds (2004 and 2009) of the Ethiopian Rural Household Survey. According to this study, both participation and intensity are estimated to be higher for the poor. More specifically, compared to the non-poor, those who persistently fell into poverty throughout the five-year period are more likely to participate. The income share of the rural non-farm sector is higher for households owning less number of oxen. Besides poverty indicators, controls such as credit, crop and labor prices, as well as locational and time dummies, are found as other significant determinants of both participation and intensity.

Abebe (2008) studied determinants of off-farm work participation decision in Ethiopia using the Ethiopian Rural and Household Survey in 1999. The results of the analysis show that human capital variables such as health and training on non-farm activities have a positive effect on the off-farm participation decisions of male members of farm households. The education status of the head has no significant impact on the participation decisions of the members of the family as most of the off-farm activities do not require formal education. This study focused only on participation and has not given attention to determinants of the income intensity from this sector. If we look at all literature cited above (Abebe, 2008; Adugna, 2009; Getachew, 2012; Browse, 2015; Tshabalala and Sidique, 2020), beside they follow the same procedure, the data used may not clearly address the current situation regarding non-farm sector in Ethiopia. While using such secondary data, things to be considered include the type and objective of the situations, purpose for which the data are collected and compatible with the present problem, whether the nature and classification of data are appropriate to our problem, whether there are no biases and misreporting in the published data. Again the sample size, sampling procedure and elements of the data are not clearly addressed in this literature.

The current study is different from those mentioned above in the following aspects. First, the primary data source is used after clear identification of the problem and objective of the study. Second, the representativeness of the sample is clearly checked after appropriate sample size determination. Third, sampling bias and misreporting during data collection were closely managed. Fourthly, both participation decision and intensity of non-farm sector were given attention. Lastly, this study is believed to be the first investigation with reference to the study area. In spite of the very importance of the rural non-farm sector, little attention has been given to it partly because of the exclusive focus of policies on the agricultural sector. Existing studies on the non-farm sector are very limited to informing policy makers in the country. Due to the foregoing, this study was carried out to investigate the factors influencing participation in non-farm work as well as the predictors of non-farm income intensity among small-scale farmers in Gida Ayana district. The findings of the study are expected to guide policy makers on measures to improve rural incomes and livelihood security.

Materials and methods

The study was undertaken in Gida Ayana district of the East Wollega Zone, Oromia National Regional State and 440km away to the West from Addis Ababa, the capital city of the country. This district is bounded by Guto Wayu woreda in the South direction, the Amhara region in the North, Limu woreda in the West and Kiramu and Abe Dongoro woredas in the East direction. The total catchment area of the woreda is about 183,063 M^2 and its climate condition is Woyinadega (48%), Dega (2%) and Kola (50%). It is located at 9°52'N and 42°37'E geographical grids (Gobena., 2019).

The study used a primary data source and respondents were selected by a two-stage random sampling procedure where at the first stage, four rural kebeles were randomly selected. At the second stage, households were selected by simple random sampling from each kebeles. Following Cochran (1977), the sample size needed for the study was calculated to be 196 households. The data collected included household, farm, and socioeconomic, demographic and institutional factors and those variables are defined in Table 1. Information on income from both farm and non-farm activities was collected.

Double-Hurdle Model of Non-Farm Income Determination

The first step in the implementation of the double-hurdle model relates to the decision or willingness to participate in non-farm work. This binary decision can be modeled as an index function using a probit model as follows:

$$Z_i^* = \omega_i'\alpha + \varepsilon_i, \text{ where, } Z_i = \begin{cases} 1, & if\ Z^* > 0 \\ 0, & if\ Z^* \le 0 \end{cases} \quad 1$$

Where,$Z_i{}^*$ is a continuous real-valued index variable for observation i, that is unobserved (latent), $Z_i$is a dichotomous variable which takes a value of 1 for the household participating in non-farm work and 0 elsewhere, ω is a vector of explanatory variables, α denotes a vector of parameters and ε is the error term. The empirical model for household decision to participate in non-farm work is specified for this study as follows:

$$Z_i = \alpha + \alpha_1\omega_1 + \alpha_2\omega_2 + \cdots + \alpha_{12}\omega_{12} + \varepsilon_i \quad 2$$

Where, Z_i measures the choices of the i^{th} household to participate in non-farm activities, $\alpha_i's\ (\alpha_1, \alpha_2, \alpha_3, \ldots, \alpha_{12})$ are parameters to be estimated by maximum likelihood method, $\omega_i's\ (\omega_1, \omega_2, \omega_3, \ldots, \omega_{12})$ are explanatory variables defined in Table 1 above and ε_i is the error term.

In the functional form of the Probit model, we assume the model takes the form $Pr(Y = 1/\omega) = \Phi(\omega_i'\alpha)$, Φ is the cumulative distribution function (CDF) of standard normal distribution.

The parameters $\alpha's$ are typically estimated by the maximum likelihood technique which for the current study adopted as:

$$L(\alpha) = \prod_{i=1}^{n}[\Phi(\omega_i'\alpha)]^{y_i}[1 - \Phi(\omega_i'\alpha)]^{1-y_i} \quad 3$$

The log likelihood is obtained by taking the log of both sides of Equation (3).

$$lnL(\alpha) = \sum_{i=1}^{n}\{y_i \ln[\Phi(\omega_i'\alpha)] + (1 - y_i)\ln[1 - \Phi(\omega_i'\alpha)]\} \quad 4$$

Because of the symmetry of the normal density, $1 - \Phi(\omega_i'\alpha)$can be expressed ad $\Phi(-\omega_i'\alpha)$. Hence, the log likelihood function will have the form:

$$lnL(\alpha) = \sum_{i=1}^{n}\{y_i \ln[\Phi(\omega_i'\alpha)] + (1 - y_i)\ln[\Phi(-\omega_i'\alpha)]\} \quad 5$$

This log-likelihood function is globally concave in α and standard numerical algorithms for optimization will converge to the unique maximum. In the Probit model, the magnitude cannot be interpreted using the coefficient because different models have different scales of coefficients. Hence, the marginal effect is used instead to interpret the model and defined as:

$$\frac{\partial Pr(y=1)}{\partial \omega_j} = \Phi(\omega'\alpha)\alpha_j \quad 6$$

The marginal effects reflect the change in the probability of $y = 1$ given a unit change in an independent variable, keeping other covariates fixed. Coefficients and marginal effects of the Probit model have the same sign.

The second equation in the double-hurdle relates to the intensity of non-farm income earned by the respondents. The second hurdle equation can be estimated using a regression truncated at zero (similar to a Tobit model) with the following formulation:

$$y_i^* = x_i'\beta + \varepsilon_i, \text{ where, } y_i = \begin{cases} y_i^* & if\ y^* > 0 \\ 0 & if\ y^* \le 0 \end{cases} \quad 7$$

Where, y represents the observed income from non-farm works which depend on the latent variable y^*being greater than zero and $x_i$denotes a vector of explanatory variables, β represents a vector of parameters to be estimated and $\varepsilon_i$is a random error term. Empirically, the truncated regression model is specified for this current study as follows:

$$Y_i = \beta_0 + \beta_1x_1 + \beta_2x_2 + \cdots + \beta_{12}x_{12} + u_i \quad 8$$

Where, $y_i$is the intensity of non-farm income of the i^{th}household, $\beta_i's$ $(\beta_1, \beta_2, \ldots, \beta_{12})$ are parameters of truncated regression to be estimated, $x_i's$ $(x_1, x_2, \ldots, x_{12})$ are explanatory variables defined in Table 1 above and u_i is the random error term.Ordinary Least Square Estimation on the truncated data will cause biases.

The model that produces an unbiased estimate is based on the Maximum Likelihood Estimation.The likelihood function of the truncated regression for i[th] observation is given by:

$$L_i = \frac{\frac{1}{\sigma}\phi\left(\frac{y_i - x_i'\beta}{\sigma}\right)}{\Phi\left(\frac{x_i'\beta}{\sigma}\right)} \qquad 9$$

The log likelihood function is given by:

$$LogL(\beta,\sigma) = \sum_{i=1}^{N}\log L_i = -\frac{N}{2}[\log(2\pi) + \log(\sigma^2)] - \frac{1}{2\sigma^2}\sum_i^N \varepsilon_i^2 - \sum_{i=1}^{N} log\left[\Phi\left(\frac{x_i'\beta}{\sigma}\right)\right] \qquad 10$$

The values of (β, σ) that maximizes Log L are the ML estimators of the Truncated Regression.

Results and discussion

The summary statistics of the respondents in Table 2 shows that only 34.2% of the respondents were engaging in non-farm work. The result further depicts that the majority of the respondents in the study area were male-headed (83.7%). Access to credit is not well practiced as 63.8% of the respondents reported that they do not have its access. On the other hand, 65.3% of the respondents reported that they have access to extension services. Access to market information is well expanded in the study district. More than half of the respondents were using fertilizer for crop production.

The respondents had approximately 4 years of formal education on average with a standard deviation of 3.39, while the mean household size per household is found to be 4 members with a standard deviation of 2.05. The maximum education level attained by the respondent's Diploma level which needs staying in the school for 15 years. The average size of land owned by each household was 3.72 hectares with a standard deviation of 1.49. On average, a household had 3 Oxen with a standard deviation of 1.42, while the minimum and the maximum number of Oxen ownership were 0 and 6, respectively. For the household to arrive at the nearest market and extension service, it took 51.34 and 55.10 minutes on the average walk on foot, respectively (Table 3).

Table 1. Definition of selected variables of the study.

Dependent variables	Definition
Decision to Participate in non-farm work	A dummy variable coded as 1 = yes and 0 = no
Non-farm income	Amounts of non-farm income earned in 1000 ETB
Explanatory Variables	Definition
Sex of household head (X_1)	A dummy variable coded as 1 if male and 0 if not
Age of household head (X_2)	A continuous variable measured in years
Education level of household head (X_3)	A continuous variable representing year of schooling
Household size (X_4)	A continuous variable measured in number
Land size of household head (X_5)	A continuous variable measured in hectare
Number of Oxen (X_6)	A continuous variable measured in number
Access to credit (X_7)	A dummy variable coded as 1 = yes and = no
Access to extension service (X_8)	A dummy variable coded as 1 = yes and 0 = no
Distance to extension service (X_9)	A continuous variable measured in minute
Distance to the nearest market (X_{10})	A continuous variable measured in minute
Access to market information (X_{11})	A dummy variable coded as 1 = yes and 0 = no
Using fertilizer (X_{12})	A dummy variable coded as 1 = yes and 0 = no

Determinants of participation in non-farm workand its intensity

The double hurdle model was applied to detect significant factors determining households' decision to participate in non-farm work and factors influencing the intensity of non-farm income from different sources. The first hurdle (probit model) detected some significant variables determining households' decision to participate in non-farm work.

The second hurdle (truncate regression) identified potential variables influencing the intensity of non-farm income. The results from both hurdles were interpreted and discussed as follows.

Table 2. Summary statistics of respondents by selected (Dummy variables).

Variables	Item	Frequency	Percent
Participation in non-farm activities	Yes	67	34.2
	No	129	65.5
Sex of household head	Male	164	83.7
	Female	32	16.3
Aces to credit	Yes	71	36.2
	No	125	63.8
Access to extension service	Yes	128	65.3
	No	68	34.7
Access to market information	Yes	184	93.9
	No	12	6.1
Use of fertilizer	Yes	116	59.2
	No	80	40.8

Source: Author's computation (2021).

Education of household head: This variable positively and significantly influenced households' participation in non-farm income-generating work. The result of the marginal effect showed that, other variables being constant, the probability of engaging in non-farm work increases by 1.1% as education of household increases by one year. The implication of this result is that literate households appreciate the importance of non-farm work to increase household income and are more likely to engage in different non-farm works than illiterate households. This result is in line with the result by Raphael and Matin (2009) who examined that households who are disadvantaged in terms of education are constrained in their ability to participate in more lucrative off-farm activities. The result is also consistent with Javier (2001) who argued that the higher the education level, the greater the incentive to commit time to non-farm self-employment activities as well non-farm wage employment. The same result was found by Ibekwe *et al.* (2010) who argued that households with higher education are more likely to seek non-farm employment in rural Nigeria. Number of Oxen owned: Oxen ownership is an important positive and significant determinant of households' participation in non-farm work and the intensity of income from this sector. Accordingly, the marginal effect of this variable conveyed that as the number of Oxen owned by the household increase by one, the probability of households' decision to participate in non-farm income generating works increases by 6.8%. Similarly, the result from truncated regression showed that, other things being constant, the non-farm income of households increases by 0.063 (in thousands of Ethiopian Birr) as the number of oxen increases by one.This result is contradictory to the result by Getachew (2012) who found that the income share of the rural non-farm sector is higher for households owning less number of Oxen. This is because Ox is an important factor of crop production and is sometimes considered as 'capital' together with its plough complements.

Table 3. Summary statistics of respondents by selected (Continuous variables).

Variables	Min.	Max.	Mean	St. Dev.
Age of household head	19.00	80.00	38.92	9.60
Education of household head (Year)	0.00	15.00	3.63	3.39
Family member 15-65 years old	1.00	11.00	3.47	2.05
Total land holding size in hectare	0.50	6.00	3.72	1.49
Number of oxen owned by household	0.00	6.00	2.64	1.42
Distance to extension service (Minute)	5.00	120.00	51.34	27.31
Distance to nearest market (Minute)	10.00	130.00	55.10	33.77

Source: Author computation (2021).

Access to credit: The availability of funds to the household through access to credit is also a positive determinant for participation in non-farm income-generating work. The result of the marginal effect of this variable indicated that households having credit access were 6.7% more likely to participate in non-farm income generating works than those who do not have access to credit. Abebe (2008) argued that the amount of credit given to households would increase the probability of working off-farm. On the other hand, a policy brief report in Ethiopia underlined that credit is a source of income that boosts the capacity of rural households to purchase yield-enhancing agricultural inputs and has remained to be a shortcoming for poorer households in intensifying the farm sector.

Table 4. Maximum likelihood estimates of double hurdle model for participation in non-farm work and intensity of non-farm income.

Variables	First hurdle (Probit model)			Second hurdle (Truncated regression)	
	Coeff.	dxdy	Std. Error	Coeff.	Std. Error
Sex of household head (1 = Male)	-0.160	-0.051	0.255	-0.048	0.076
Age of household head (Year)	0.018	0.006	0.011	0.004	0.003
Education of household head (Year)	0.036**	0.011	0.119	0.020	0.037
Family size (Number)	-0.083	-0.027	0.051	-0.025	0.016
Land size holding (Hectare)	-0.005	-0.002	0.070	0.001	0.021
Number of oxen	0.215*	0.068	0.079	0.063*	0.023
Access to extension service (1 = Yes)	0.286	0.091	0.209	0.070	0.061
Access to credit (1 = Yes)	0.209**	0.067	0.197	0.050	0.060
Distance to extension service (Minute)	0.002	0.006	0.003	0.001	0.001
Distance to the nearest market (Minute)	0.008	0.003	0.003	-0.002**	0.001
Access to market information (1 = Yes)	0.765**	0.244	0.333	0.229**	0.1021
Fertilizer use (1 = Yes)	-0.436**	-0.139	0.195	-0.128**	0.061
Constant	-0.209		0.966	0.628**	0.295
Sigma				*0.433*	*0.019*
For Probit For truncated regression					
LR Chi2 = 41.22, Log likelihood = -138.865			*Wald Chi2 = 39.43, Log likelihood = -155.456*		
*Significance level: *(1%) and **(5%), dxdy = marginal effect*					

Source: Author computation (2021).

Distance to the nearest market: Access to infrastructure is very crucial for mobility from place to place in diversifying livelihood, especially in rural areas. The availability of a market nearby the homestead helps the rural households to engage in different income-generating works. This study found that distance to the nearest market negatively and significantly influenced the intensity of non-farm income. As the distance to the nearest market increases by one unit, the level of non-farm income decreases by 0.002 (in thousands of Ethiopian Birr). The probable reason for this outcome may be that majority of the non-farm works are found in urban than rural areas. Hence, households who are far from the market center are less likely to engage in non-farm income generating works than those households near to the market center and this, in turn, reduces the intensity of income obtained from this sector. The result obtained here is contradictory with Tshabalala and Sidique (2020) who argued that non-farm enterprise income increases with the distance to markets.

Access to market information: As information is the backbone for the world economy in general and for the individual endeavor in particular, market information is expected as highly significant predictor for non-farm income diversification. Accordingly, this study found that access to market information positively and significantly influenced households' participation in non-farm work and the intensity of income from this sector. The respective results from both hurdles showed that having access to market information increases the likelihood of engaging in non-farm work by 24.4% and increases the intensity of income from the sector by 0.229 (in thousands of Ethiopian Birr), keeping the effect of other variables constant. The implication of the result is that those households having access to market information can engage in non-farm activities which best meet their income requirements based on different alternatives. It provides the best alternatives for those having its access in which they can be beneficiaries in generating non-farm income.

Use of fertilizer: The use of fertilizer negatively and significantly influenced households' participation in non-farm work and the intensity of income from the sector. Accordingly, as households use fertilizer for their crop production, their likelihood to engage in non-farm work decreases by 13.9%, keeping the impact of other variables constant. Similarly, as households use fertilizer, the intensity of income from this sector decreases by 0.128 (in thousands of Ethiopian Birr), keeping other variables constant. Agricultural inputs such as fertilizers are believed to boost farm outputs which increase the income from the farm sector. Households who use fertilizer are less likely to engage in non-farm income-generating activities as far as they rely on farm income which increases their level of farm income than those who do not use fertilizer.

Conclusion

The preset objective of the study was to assess factors influencing participation in non-farm work as well as the predictors of the intensity of non-farm income using the double hurdle model. The result reveals that only 34.2% of the sampled households engage in non-farm work based on the information collected from 196 households. The non-farm works are performed as a complement to agriculture part-time or during the agricultural off-seasons while including handcraft selling, trading and small construction in rural areas. Rural households need to engage in non-farm works due to lack of agricultural land, low earnings and for obtaining additional income to invest in agriculture. The econometric result from the first hurdle depicts that better-educated households, households with more number oxen as well as those households having accesses such as credit fund and market information, are more likely to engage in non-farm work. On the other hand, households who use fertilizer for crop production are less likely to participate in the non-farm income-generating farm than those households who do not use fertilizer. The result from the second hurdle confirms that the intensity of non-farm income increases with the increase in the number of oxen and access to market information while decreasing with the increase in distance to the nearest market center and use of fertilizer. Based on the result of this study, households are recommended to engage in different sources of income-generating works since farm income alone is not enough to fulfill their family's basic requirements for running livelihood. Additionally, local agricultural sector and development agents need to expand rural infrastructure for the free mobility of the farmers between rural areas and market centers to engage in non-farm works.

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