Labor allocation to Non-agricultural Activities in Rural Ethiopia: A Gender Perspective[1]

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Abstract

The aim of this paper is to identify factors influencing labor allocation decisions of adult members of farm households in rural Ethiopia. The analysis is done using a Two Part Model (TPM) based on data pooled from the first three waves of the Ethiopian Rural Socio-economic Surveys (ERSS). The results show that labor allocation is influenced by both incentive (pull/push factors) and capacity factors such as education, land size, livestock possession and non-labor income. Besides, the results suggest that there is a gender disparity in the allocation of labor to nonagricultural activities in rural Ethiopia. That is, female members of farm households are more likely to participate in nonagricultural works, and when they do, they also work more hours than the male members. Furthermore, gender differences are observed in some factors such as education, number of infants in a household, and non-labor income that affect labor allocation decisions. Therefore, policies that aim at improving efficiency of labor allocation in rural areas should take into consideration differences in responses to various factors that affect decisions of male and female members of farm households.

Keywords: Time allocation, Nonagricultural activities, Two Part Model, Rural Ethiopia
JEL Codes: D13, J22, Q12

[1] Manuscript received: 8 July 2021
Accepted: 27 August 2021
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1. Introduction

As is common in most developing countries, a significant number of the Ethiopian population lives in the rural areas depending mainly on agriculture for their livelihoods. About three quarters of the population is engaged in agricultural activities such as crop production, livestock rearing and fishery (Schmidt and Woldeyes, 2019). However, the agricultural sector has failed to offer a sufficient means of livelihood. The sector is unable to retain the existing disguised labor force or to productively absorb additional workforce (Van Den Berg and Kumbi, 2006; Bezu and Holden, 2014). The problem of the sector is because of the high population growth that leads to persistently declining farm sizes and increasingly fragmented land possessions.

Agricultural activities in rural Ethiopia are highly characterized by subsistence production overwhelmingly dominated by smallholder farmers cultivating less than 0.5 ha using crude tools and traditional farming systems (Etea et al., 2020). Consequently, this has led to low agricultural productivity that results low income. Besides, agriculture in Ethiopia is primarily rain-fed and thus it has been challenged by recurrent climate shocks.

Consequently, individuals who are constrained by meager employment opportunities in the agricultural sector are often pushed to look for alternative employment opportunities outside farming. An increasing number of Ethiopian rural household members participate in different nonagricultural activities in order to supplement and sustain their livelihood. Yet, there is a lack of rigorous investigation about the multifaceted factors that influence such labor allocation decisions. Cognizant to this fact, the current study attempts to identify major factors influencing participation in, and the number of engagement hours dedicated to nonagricultural activities among adult members of farm households in rural Ethiopia. Furthermore, the study examines gender differences in their allocation of time and in the extent nonagricultural work participation and hours of work varies.

Considerable number of studies look into factors behind labor allocation decisions in developing countries. Yet, their analysis is limited to the extensive margin where they only look at determinants of the decision to participate or not to participate in a given rural activity, and hence they fail to further look into the factors that influence the extent of participation. Besides, previous studies have failed to take into account the fact that labor allocation to a specific rural activity may actually not represent a separate decision, rather it is the outcome of an optimization process in which allocation of time to different activities are jointly determined.

This study aims to contribute to the existing literature related to livelihood diversification strategies by examining factors that drive labor allocation to nonagricultural activities in the context of rural Ethiopia. The analysis is done both at the extensive as well as at the intensive margins using a Two Part Model based on nationally representative household survey data. Moreover, a Control Function Approach is used to address a potential simultaneity bias that may result from the interdependence of work decisions across alternative rural activities.

A thorough understanding of determinant factors that influence employment choices of adult members of farm households is of great importance to policy makers. Of particular importance is a consideration of whether there is gender inequality in labor allocation across different rural activities. The information that comes from such a study helps concerned stakeholders to come up with development programs, policies and strategies that could help them improve livelihoods in the study area.

The paper is organized as follows. The next section presents a brief review of the empirical literature from Ethiopia and identifies the existing knowledge gap. Section three sets the theoretical framework which serves as a foundation for the empirical analysis relating to time allocation decisions. Section four discusses the data and specifies the empirical strategy for the analysis. Section five presents the descriptive and econometric results followed by some discussion. The last section concludes with a discussion of results and attempts to outline possible policy implications.

2. Empirical Literature Review

There are a few studies from Ethiopia that look into labor allocation decisions in rural areas. Woldenhanna and Oskam (2001) have examined households' labor supply to nonfarm employment and they found upward sloping labor supply curves for both wage and self-employment. According to their findings, households are engaging in wage employment due to push factors while they are pulled to self-employment to gain attractive returns. Also, Lemi (2010) have studied labor allocation between on-farm tasks and off-farm employment in rural Ethiopia. The results have shown that labor allocation is heavily determined by individual, household, and their farm characteristics. Female headed households with high dependency ratio, high livestock value, and poor quality of land were found to participate less in off farm activities. The results have also shown that the intensity of off farm employment increases with land size and decreases with livestock holding.

Likewise, Bezu et al. (2014) have analyzed rural nonfarm employment choices of individuals in Ethiopia. The findings suggest that factors that influence individuals' decision to participate in nonfarm employment differ for the different types of activities. Determinants of participation in high return activities are dominated by capacity variables while determinants of participation in low return activities are dominated by push factors. Recently, Schmidt and Woldeyes (2019) have examined labor diversification in Ethiopia focusing on youth that have relatively greater probability of working in nonagricultural enterprises. Their analysis suggests that push factors are at play with regards to nonagricultural diversification, whereby those that live in less favorable agricultural potential areas, with fewer assets such as livestock, and less access to agricultural credit are more likely to seek off farm work.

Prior studies on nonfarm activities in Ethiopia are very limited to inform policy makers. Most of the studies are conducted based on household surveys with limited coverage that hardly represent the whole country (Woldenhanna and Oskam, 2001). Besides, most studies consider the household as their unit of analysis and fail to look into intra household differences in labor allocation; thus, they are not able to differentiate which family member involves in nonfarm activities. Few studies analyze gender effects by considering gender of the household head and fail to recognize the inherent differences between male and female headed households (Lemi, 2010; Bezu et al., 2014).

3. Theoretical Framework

The analytical framework for the current study is based on a modified agricultural household model suggested by Singh, Squire, and Strauss (1986). A non-separable model is used where, production, consumption, and work-related decisions are brought together into a single framework. This is suitable in the context of rural areas of developing economies where there are multiple market imperfections leading to non-separable decision (Sadoulet, De Janvry, and Benjamin, 1998).

Under the assumption of perfect labour markets, individuals choose to engage in nonagricultural activities as long as the marginal value of agricultural labor (reservation wage) is less than the income offered in the nonagricultural sector. However, in case of imperfections, the decisions to participate in non-agricultural activities are much influenced by a host of socio demographic, economic, and institutional factors.

Conceptually, the decision for allocating labor to nonagricultural activities may be influenced by incentives offered (that is, demand pull and distress push factors) and capacity factors. Employment diversification due to demand pull factors occurs as a deliberate strategy taking into account the earning difference between sectors and associated riskiness (Ellis, 1998). Individuals are motivated to participate in nonagricultural activities with the desire to accumulate wealth through the extra income generated from such activities and/or to take advantage of market and nonmarket opportunities in the nonfarm economy (Reardon, 1997; Ellis, 2000; Barrett et al., 2001).

Another set of motives comprise distress push factors, where nonagricultural employment serves as an involuntarily strategy for survival in the struggle to overcome livelihood distress under deteriorating conditions (Lanjouw and Lanjouw, 2001; Barrett et al., 2001). Employment diversification for the push reasons is generally carried out as ex ante risk management strategy and/or ex post coping mechanism against shocks that may cause transitory drops in farm income (Alobo Loison, 2015; Reardon, 1997). Farm households in rural areas of most developing countries are constrained by market imperfections such as missing or incomplete markets for factors and/or lack of formal risk management instruments. Hence, they are often pushed to engage in rural nonagricultural activities in order to self-insure themselves against the possible risks (Barrett et al., 2001).

In addition to the push and pull factors, whether and to what extent farm households are engage in nonagricultural activities also depends on capacity factors such as human and financial capital, as well as availability of infrastructure (Reardon, Berdegue, and Escobar, 2001; Bezu et al., 2014). Resource constraints related to such capacity factors become binding only where markets do not operate in a competitive way (Reardon, 1997).

The main explanatory variables to be considered for this study are chosen in order to capture main incentives and capacity factors that could influence the relative marginal values of investing labor in various activities. The focus on individual and household characteristics such as indicators of gender, age and education status; household composition (number of children in a household); wealth indicators (land and livestock holding); and exposure to covariate shocks such as drought, flood and landslides) undoubtedly play an important and direct role in determining the way people allocate their time. Furthermore, gender interaction is included for some of the variables which are presumed to have differential impacts on the labor allocation decisions of male and female members of a household. Specifically, education status, number of infants and non-labor income are made to interact with gender. The region and year effects are controlled. The list of variables and summary statistics is presented in Table A1 in the Appendix.

All the aforementioned variables may affect both the reservation and non-farm wage. Hence, the direction of the influence on non-farm employment is indeterminate. Variables that raise the reservation wage reduce the probability and level of participation in non-farm work. By the same token, the variables that raise the value of marginal product of labour in non-farm employment have the opposite effect.

4. Methodology

4.1 The Data

This paper uses pooled data from Ethiopian Rural Socio economic Surveys (ERSS) of the World Bank's Living Standards Measurement Study - Integrated

Surveys on Agriculture (LSMS-ISA) database. It is the result of nationally representative, household level panel data surveys covering three rounds over a time span of five years, from 2010/11 to 2014/15. The data have a section for time use data collected during the post-harvest season for the major agricultural season in many parts of the country (January-May). This section has details on how individuals spend their time on different rural activities (collecting fuel wood, fetching water, working on agricultural activities, nonagricultural activities, temporary/casual work or salaried job, and unpaid apprentice). Thus, the data are helpful to make precise analysis of the labor allocation decisions.

A restricted sample was used for analysis considering only adult members of households (between 15 and 65 years) that consists of 3450 individuals observed in three waves, resulting in a pooled sample of 10350 adults.

4.2 Empirical Strategy

In this paper, a Two Part Model (TPM) is used to analyze labor allocation decisions of adult members of farm households. TPM is a more flexible alternative than the Tobit model (Tobin, 1985) or Heckman selection model (Heckman, 1979). TPM is suitable to sequentially model the participation decision (whether or not to participate in the nonagricultural work) and the intensity of participation (amount of time allocated by participants). TPM allows including different covariates in the two decisions and does not assume the determinants of the binary participation decision to similarly explain the intensity of participation decisions (Cragg, 1971; Duan et al., 1984). This is in contrast to Tobit model, which is restrictive assuming a single decision process whereby both decisions are determined by the same underlying process (Tobin, 1985).

Furthermore, TPM allows the possibility of zero observations in the first and second hurdles. Unlike the Tobit model, which is restrictive in interpreting the zero values for nonparticipation as corner solutions in utility maximization (Amemiya, 1984), TPM considers the fact that zero observations may arise due to behavior of respondents, deliberate choices, sampling errors, absenteeism or random circumstances. Zeros may arise due to the short reference period of the survey time relative to the period over which participation decisions are made (Stewart, 2013).

Heckman's sample selection model is a candidate in such a context but it is restrictive assuming that the zeros denote censored values of the positive outcome and none of the zero observations may be due to a corner solution (Heckman, 1979; Belotti et al., 2015). Furthermore, Heckman's model only considers those who chose positive hours of work, and does not observe anything about the people who do not participate in a given work (Heckman, 1979). On the other hand, TPM allows the inclusion of all observations in the sample; where it is still possible to observe those who do not work, but record zero hours of work.

TPM has been used to model labor supply decisions in developing countries. For instance, Matshe and Young (2004) has applied TPM to model off farm labor allocation Zimbabwe. Similarly, Ibrahim and Srinivasan (2011) has used the double hurdle model to examine the off farm labor supply decisions of rural households in Nigeria. Recently, Salmon and Tanguy (2016) has employed the hurdle model to investigate the impact of electrification on male and female labor supply decisions within rural households in Nigeria.

The Two Part Model (TPM) used in this paper can be written as follows:

$$p_i^* = z_i'\gamma + \varepsilon_i \ , \quad p_i = \begin{cases} 1 \text{ if } & p_i^* > 0 \\ 0 \text{ otherwise} \end{cases} \tag{1}$$

$$h_i^* = x_i'\beta + u_i, \qquad h_i = \begin{cases} h_i^* \text{ if } & h_i^* > 0 \text{ and } p_i^* > 0 \\ & 0 \text{ otherwise} \end{cases} \tag{2}$$

The first part, Equation 1, is a binary model which captures the likelihood of participation with a dummy variable that takes a value of one if individual i participates in any nonagricultural work during the reference period, and a value zero if no participation is recorded. p_i^* is a latent variable associated with nonagricultural work participation and it represents the binary censoring, while p_i is the corresponding observed value.

Equation 2 presents the second part which is a continuous model for the decision on the intensity of participation conditional on the participation decision, explicitly considering that the observed hours of nonagricultural work (h_i) is censored at zero. The actual observed hours of work (h_i) equals the unobserved latent value associated with potential hours of nonagricultural work (h_i^*) only when a positive hour of work is reported; otherwise, it takes the value of zero. In this model, a two stage process must have been completed before a positive hours of work is observed: first, the individual has decided to participate in nonagricultural work; and second, this individual has allocated some amount of time to nonagricultural work (Cragg, 1971).

z_i' *and* x_i' represent vectors of variables that explain the participation and hours of work decisions, whereas γ and β are the corresponding vectors of parameters.

ε_i and u_i are the error terms. In the model originally proposed by Cragg (1971), error terms of the two hurdles are assumed to be uncorrelated and normally distributed. But, the TPM used in this paper does not make any assumptions about correlation between the errors. The errors are assumed to follow a bi-variant normal distribution. That is,

$$\begin{pmatrix}\varepsilon_i \\ u_i\end{pmatrix} \sim BVN\left[\begin{pmatrix}0 \\ 0\end{pmatrix} \quad \begin{pmatrix}1 & \rho^{\sigma} \\ \rho^{\sigma} & \delta^2\end{pmatrix}\right].$$

This study follows the formulation presented by Jones (1992) in which hurdles are not independent. If information on censoring is available, the likelihood function can be written as:

$$L = \prod_{h=0}\left\{1 - \Phi_2\left(z_i'\gamma\,, \frac{x_i'\beta}{\sigma_h}, \rho\right)\right\} \prod_{h>0}\left\{\Phi_1\left\{\frac{z_i'\gamma + \frac{\rho}{\sigma_h}(h_i - x_i'\beta)}{\sqrt{1-\rho^2}}\right\}\frac{1}{\sigma_h}\emptyset\left(\frac{h_i - x_i'\beta}{\sigma_h}\right)\right\} \quad \textbf{(3)}$$

where Φ_1 is the normal cumulative distribution function, Φ_2 is the bivariate normal cumulative density, and and $\emptyset$ is the density function of the normal distribution.

5. Results and Discussion

5.1 Descriptive Results

Table A1 in the Appendix reports the summary statistics for the variables included in the analysis on the restricted sample of adult members of households (between 15 and 65 years). For the sake of parsimony, in what follows details are provide only for the outcome variables of our analysis that indicate participation and level of participation in rural nonagricultural activities. The data have information on hours of nonagricultural work recorded for each individual during the seven days preceding the survey. Nonagricultural activities include all economic activities in rural areas except primary agriculture, livestock, fishing and hunting. They include all secondary and tertiary sector employment of both permanent and casual nature, and they can be categorized into nonagricultural self-employment, wage employment and unpaid work.

More than one-third of the adults in the sample have reported zero hours of work, may be because they were unable to work in the reference week or they may choose not to work with the given amount of economic incentives. On one hand, agriculture remains by far the primary source of employment in rural Ethiopia (61 percent of the adults in the sample reported to have allocated some time to agricultural activities in the reference week). On the other hand, working in nonagricultural work is still rare (only 12 percent of the adults report to have spent positive hours in nonagricultural activities in the reference week). Conditional on working, an individual in rural Ethiopia allocates, on average, 24 and 22 hours a week for agriculture and nonagricultural activities respectively.

Table 1: Labor allocation across rural activities in Ethiopia
(Summary statistics on pooled sample disaggregated by gender)

	Pooled-Sample (N=10530)	Sub-Sample	
		Male (N=5034)	Female (N=5316)
Incidence of Work (Weighted Percentage of Individuals that Report Positive Hours of Work)			
Agricultural Activities	0.61	0.72	0.51
Nonagricultural Activities	0.12	0.11	0.14
Any Rural Activity (Agri/Non-Agri/Temporary/Paid/Unpaid)	0.68	0.78	0.59
Intensity of Work (Weighted Mean Weekly Hours Allocated, Conditional on Working)			
Hours Spent on Agricultural Activities	23.96	26.32	20.61
	(16.69)	(16.56)	(16.27)
Hours Spent on Nonagricultural Activities	22.4	19.49	25.06
	(16.7)	(15.18)	(17.63)
Hours Spent on Any Rural Activity	28.68	31.03	25.51
	(21.23)	(20.79)	(21.39)

Note: Statistics based on the restricted sample adult members of households (15-65 years) in rural Ethiopia.
Standard deviations are reported in brackets.

The statistics reported in Table 1 clearly indicate that time use patterns vary by gender. Agricultural activities are more commonly carried out by male than female household members. Approximately 72 percent of male members are engaged in agricultural activities as compared to 51 percent of female members. Adult male members of rural households allocate, on average, 26 hours per week to agricultural activities while female members allocate only about 21 hours per week to agricultural activities. On the other hand, slightly higher percentage of female (14%) as compared to men (11%) reported to have allocated positive labor hours to nonagricultural activities in the reference week. Besides, the reported weekly average hours spent on such activities is higher for female (25 hours) than male (20 hours).

The total workload of men seems to exceed that of women in rural Ethiopia. Approximately 78 percent of adult male (relative to 59 percent of the female) have reported positive hours of work in the reference week. On average, men spend five more hours in different agricultural and nonagricultural activities as compared to their women counterparts.

when analyzing labor allocation, it is important to consider household activities in rural areas where access to basic infrastructure is usually limited and traditional gender roles are deeply rooted. However, the analysis in this paper does not cover such activities due to data paucity. Yet, it is well established that women in rural Ethiopia are predominantly engaged in time consuming household activities, which ultimately limit their time available to other works. Hence, once such household works are considered, the total workload on women is expected to far exceed those of men.

5.2 Econometric Regression Results

These papers conduct extensive analysis on nonagricultural labor market participation and amount of time allocated using Two Part Model (TPM) regression technique. Parameter estimates have been obtained using the Stata user written command twopm. The regression adjusts for the complex sample design of the ERSS data in computing the parameter estimates and the standard errors of those estimates.

It is important to check whether the model fits the data by exploring the assumptions of the model specification. The distribution of the dependent variable tested by plotting a histogram for the nonagricultural work participants (see Figure A1). As expected, the distribution is skewed to the right which has direct implications on normality of the error terms. TPM assumes that unobserved errors are normally distributed in the positive part. The maximum likelihood estimator may be inconsistent when the normality assumption fails. Beyond the graphical examination of the data, the normality assumption is also checked with Shapiro-Wilk W test using residual estimates from a truncated regression model. The normality assumption is rejected as the test yields very small p-value which is confirmed with the kernel density plot of residuals, which supports non-normality in residuals (see Figure A4). One way to relax the normality assumption is to use non-normal distributions, such as the log-normal or the gamma distribution.

The first part of the TPM is analyzed with a Probit model. The results are not sensitive to the model used in the first part; running a Logit model gives identical results. The second part is analyzed with generalized linear model (GLM) employing the log-link (as well as square root-link) between the expected value of the dependent variable (hours of nonagricultural work) and the linear index of covariates, assuming the random component of the outcome follows gamma distribution. Gamma distribution has a variance function that is proportional to the square of the mean function. It is usually more appropriate than the normal distribution when data are skewed, especially a positively skewed. Appropriate tests are done to check the extent to which the presumed structure of the model fits the data in terms of the link and distribution assumptions. The specification tests for the positive hours of nonagricultural work are reported in Table 2.

Table 2: GLM specification tests: link and distribution

Link: Log **Family: Gamma**	
Test for link function Pregibon link test	-0.0705 (0.055)
Modified Park test: $\lambda 2$(p-value) ν coefficient	1.5091
ν = 0 : Gaussian	59.15 (0.0000)
ν = 1 : Poisson	6.73 (0.0095)
ν = 2 : Gamma	6.26 (0.0124)
ν = 3 : Inverse Gaussian	57.72 (0.0000)

Source: Author's own computation

5.2.1 Specification tests for Generalized Linear Model (GLM)

The GLM specification requires to define the link function that characterizes how the conditional mean is related to the set of covariates. In order to assess which GLM link makes the dependent variable (hours of nonagricultural work) symmetric, the dependent variable is transformed and the histogram is checked. The untransformed dependent variable has a distribution that is skewed to the right, the log-transformation is skewed to the left while the square root transformation yields fairly symmetric distribution (see Figures A1, A2 and A3).

The log-linear model transformation is preferred over linear in the estimations. First, the link test is performed (Pregibon, 1980) in examining the GLM specification. The link test refits the model using the predicted linear index and its square as covariates. The parameter estimate is found to be very small and insignificant (see Table 2). As a result, misspecification is rejected at any level of significance, suggesting that the link is correctly specified and so there is no need to include the square term as additional explanatory variable.

Finally, a modified park test is used to assess how variance is related to the mean. The test is done by regressing logarithm of the untransformed square errors from the GLM model on the logarithm of the predicted outcomes. The test constitutes evaluating the value of the resulting parameter estimates which could be close to 0, 1, 2 or 3 implying the use of Gaussian, Poisson, Gamma or Inverse Gaussian distribution, respectively. According to the modified park test, where the coefficient (1.5091) is found to be close to 2, Gamma proves to be the most appropriate distributional family to model positive hours of nonagricultural work (see Table 2).

5.2.2 Results from Two Part Model (TPM)

Results from the two-part model (TPM) with log-link and gamma distribution are presented in two parts. The first part presents coefficient estimates of the Probit version of TPM (for the analysis at the extensive margin: the probability of participation in nonagricultural activity); the second part presents coefficient estimates of the GLM version of TPM (for the analysis at the intensive margin: weekly hours allocated to nonagricultural work by the participants)1. The marginal effects based on the combined results are presented in Table 3 herein below.

Model 1 presents results for covariates where the effect of hours of agricultural work is not controlled for while it is controlled for in Model 2. The former will be discussed herein below while the latter will be discussed under section 5.2.3.

[1] The complete results for the first and second part are not presented in this paper. But they can be presented upon request.

Table 3: Results from two-part model with log-link and gamma distribution (Marginal effects based on the combined results from the first and second part of TPM)

	MODEL 1	MODEL 2
Female	1.99***	-0.27
	(0.34)	(1.09)
Age	0.24***	0.37***
	(0.07)	(0.09)
Age Squared	-0.00***	-0.01***
	(0.00)	(0.00)
Educ_Status	1.61***	0.96**
	(0.24)	(0.38)
No of Child(<6yrs)	0.61***	0.57**
	(0.21)	(0.23)
No of Child(6-15yrs)	-0.02	-0.15
	(0.13)	(0.17)
Land Holding (Relative to Marginal < 0.5 Ha)		
Smallholder (0.5-2 Ha)	-0.73***	-0.57*
	(0.27)	(0.29)
Largeholder (> 2 Ha)	-0.71	-0.58
	(1.13)	(1.13)
Livestock_Holding	-0.21*	-0.10
	(0.10)	(0.10)
Ln_Nonlabor_Income	0.01	0.01
	(0.05)	(0.06)
Covariate_Shock	-0.25	-0.41
	(0.29)	(0.37)
Region Dummy		
Tigray	-0.13	-0.14
	(0.92)	(0.93)
Amhara	-1.12	-0.42
	(0.79)	(0.63)
Oromia	-1.09	-0.77
	(0.73)	(0.66)
SNNP	-1.52**	-1.20*
	(0.72)	(0.65)

	MODEL 1	MODEL 2
Year Dummy (Relative To 2011)		
Yr_2013	-3.53***	-3.62***
	(0.59)	(0.60)
Yr_2015	-4.14***	-4.52***
	(0.44)	(0.48)
Gender Interaction Terms		
Female*Educ_Status	-0.94***	-0.64*
	(0.34)	(0.35)
Female*Child(<6yrs)	-0.97***	-0.89***
	(0.21)	(0.21)
Female*Ln_Nonlabor_Income	0.20**	0.20**
	(0.08)	(0.08)
Control For Interdependence in Work Decisions		
Agr_Hours		-0.03***
		(0.01)
Predicted Residual		-0.19**
		(0.09)
Observations	10350	10350

Gender is the major variable of interest for the analysis indicated by a dummy variable which takes a value of one for female members of a household, and zero otherwise. According to the result, female are more likely to participate in nonagricultural activities and conditional on participation, than their male counterparts. Similarly, females work longer hours in nonagricultural activities than their male counterparts. The marginal effects for the gender dummy implies that adult female involve in nonagricultural activities significantly more than male by about 1.99 hours (see Table 3). Although female are found to work more than male at all ages, the difference is much greater for elderly than young perhaps due to the assumed log-link (see Figure A5).

Nevertheless, the response is tempered with when there are infants in the household, as implied by the negative significant coefficient of the interaction term for gender and number of infants in the household. That is to say, adult female from households with many infants are less likely to engage in nonagricultural work as compared to their male counterparts, probably because taking care of infants is mainly in the female's domain of work and it is time consuming. In contrast to findings of studies, raising children and nonagricultural work are not necessarily competing activities in rural areas of developing countries, where there is an extended family that support in taking care of children (Salmon and Tanguye, 2015).

Most of the control variables have the expected signs. Age captures the effect of experience which is believed to affect an individual's potential productivity. According to the results reported in Table 2, age is statistically significant and it has the expected positive sign while age squared has a negative sign, implying that an increase in age is translated to higher expected hours of nonagricultural work until 37 years (see Figure A6). Naturally a person would gradually start losing job opportunities after reaching a certain age, or it may be due to rigidity in shifting of activities for the elder persons, or because the demand for leisure increases at older ages (as suggested by Ibrahim and Srinivasan, 2011). The finding is consistent with the findings of Abdulai and CroleRees (2001) in their study of households in Mali. According to their findings, the likelihood of participation in nonagricultural activities first rises with age and then declines after reaching peak age. Similar results are reported by Nagler and Naudé (2017) based on their analysis of World Bank data from Ethiopia, Malawi, Niger, Nigeria and Uganda. They found older cohorts to be more likely to engage in nonfarm activities, reflecting the fact that many of who are less than 25 years old are still attending school.

Education is expected to increase the marginal value of time and reservation wage as it enhances the range of work related skills, the ability to acquire new skills and makes individuals more employable (Reardon, 1997). The result in this paper confirms the positive effect of education. Literacy increases the likelihood of participation in nonagricultural work, as well as the hours of nonagricultural work conditional on participation. The negative coefficient for the interaction term of gender and education implies that the magnitude of the effect of education is relatively lower for female compared to male members of farm households (see Model 1 in Table 3).

The existing discourse evidenced in rural Africa shows that education enhances nonagricultural work participation, especially in more remunerative salaried and skilled employment (Barrett et al., 2001; Lanjouw and Shariff, 2004;

Van Den Berg and Kumbi, 2006). Salmon and Tanguy (2016) have shown that educated individuals in Nigeria are likely to prefer to work outside agriculture. Also, Bezu et al. (2014) have identified education to be the most important factor that positively influences participation in all types of nonagricultural employment in Ethiopia.

Land and livestock possessions are important resources for agriculture and they are the main indicators of wealth in rural Ethiopia. According to the results, conditional on participation, and an increase in land size are associated with a reduction in hours of nonagricultural work for members of households with better agricultural resources (such as large land size of 0.5-2 ha) relative to less endowed households (such as those with small land size of less than 0.5 ha). The study result suggests that land constraint, which is one of the push factors to engage in nonagricultural activities, is relatively relaxed for members of households with better land holdings. On the other hand, households with large land size may choose to specialize in agricultural production, which is labor intensive in case of Ethiopia; thus, may face more binding labor constraints than those households with smaller landholdings. The finding is of course in contrast to some of the earlier findings such as Abdulai and CroleRees (2001) for Mali, Ellis (2000) for developing countries, while it is consonant to the findings of Woldenhanna and Oskam (2001) for Ethiopia.

Income is an important determinant of labor allocation decision. In the analysis, the non-labor income is controlled as other incomes as it may give rise to endogeneity problems. Furthermore, non-labor income is more relevant given the increasing flows of remittances and other transfers in the context of Ethiopia. Non-labor income may help recipient households by relaxing liquidity constraints or it may raise reservation wages and discourage participation in nonagricultural activities. The result from TPM also show that an increase in non-labor income of a household is translated to higher expected hours of nonagricultural work but it is due to higher likelihood of participation, rather than how much actual participants worked. The result is observed only for female members of farm households as indicated by a statistically significant positive coefficient of the interaction term of gender and non-labor income (see Table 3). The result, however, is in contrast to the findings of studies in many rural areas of developing countries with noncompetitive labor markets with high unemployment (Azizi, 2018).

5.2.3 The Control Function Approach (CFA) to addressing simultaneity bias in labor allocation

Hours spent in each rural activity may actually not represent a separate decision, rather are outcomes of an optimization process in which allocation of time to different activities are jointly determined. So, it is important to assess the impact of each type of work on the other to know to what extent the decisions are interrelated. Thus, in this paper, hours of agricultural work are included as an explanatory variable for the hours of nonagricultural work decision in order to account for potential interrelatedness of work decisions. However, this may result in a simultaneity bias since hours of agricultural work may relate with unobservables. Such biases are corrected by using the Control Function Approach (CFA), which entails estimation in two stages (Wooldridge, 2012). First, the reduced form equation for potentially endogenous variable (hours of agricultural work) is estimated. Then, hours of nonagricultural work are analyzed with hours of agricultural work and the residual from reduced form model as additional covariates in the structural model.

Control Function Approach (CFA) requires an exclusion restriction. That is, some strictly exogenous covariates need to be excluded from the structural model of hours of nonagricultural work to be used as instruments with other covariates in the reduced form model. A measure of temperature (weather indicator) and access to extension program are used as instruments as they are exogenous and unobservable ability is presumably independent of such variables. They affect nonagricultural activities only through their effect on agricultural activities.

In the analysis, the predicted residual from the reduced form equation is found to be significant, indicating that the variable for hours of agricultural work is actually endogenous. Thus, the predicted residual is kept as extra regressor so that remaining variation in the endogenous variable would not be correlated with unobservables.

The statistically significant negative coefficient for hours of agricultural work suggests trade-off in time allocation decisions in rural Ethiopia. Though, this coefficient is statistically significant, its impact in magnitude is very small. An hour increase in agricultural work translates to only 0.03 (less than two minutes) lower expected hours of nonagricultural work. The amount of hours devoted to nonagricultural activities seem to be constrained very marginally by the amount of hours allocated to agricultural activities (see Model 2 in Table 3).

Even after properly controlling for simultaneity bias related with the interrelatedness of agricultural and nonagricultural work decisions, the effects of most of the incentive and capacity factors still hold, with slight declines in magnitudes. Although gender is no more significant, there is still difference in response to the various factors that affect the labor allocation decisions of male and female members of farm households in rural Ethiopia.

6. Conclusion

The study examines the labor allocation decisions of adult members of farm households in rural Ethiopia using data pooled from the first three rounds of Ethiopian Rural Socio-economic Surveys (ERSS). The analysis is done using Two Part Model (TPM), which provides a more realistic model of the labor market by distinguishing between the participation and intensity of participation.

The descriptive analysis displays gender disparity in the allocation of labor time between agriculture and nonagricultural activities in rural Ethiopia. Agricultural activities are more commonly carried out by male members of farm households. On the other hand, female members of farm households participate more and spend longer hours in nonagricultural activities than their male counterparts. The econometrics analysis confirms that gender is, indeed, one of the important individual characteristics associated with labor allocation decisions in rural Ethiopia. Female members of farm households are more likely to participate in nonagricultural activities; and conditional on participation, they spend more hours than their male counterparts. However, female members of households with many infants are less likely to participate in nonagricultural activities and allocate relatively shorter hours than male members do, on conditional participation.

Besides, labor allocation is affected by both incentive (pull/push factors) and capacity factors such as education, land size, livestock holdings and non-labor income. Gender disaggregated analysis shows difference in response to the various factors that affect the labor allocation decisions of male and female members of farm households in rural Ethiopia. For instance, education is found to increase the likelihood of participation in nonagricultural activities as well as the hours of work for both male and female members, with relatively higher increase for male than female members of farm households. Similarly, non-labor income is found to increase the probability of participation in nonagricultural activities only for female members of rural farm households.

There are some caveats which should be kept in mind when considering the results discussed above. First, wage is not included in the model because of limited records in the data as most of the nonagricultural works in rural areas are informal and non-monetary payments for labor is common. It is difficult to calculate shadow wage rate for those who do not work during the survey period based on the limited records for the very few who worked. Instead, exogenous variables that affect individual's shadow price of time and the reservation wage rate are included.

Second, the analysis in this paper does not cover time allocated to household chores due to data paucity. ERSS data does not provide sufficient information on such activities on which rural women spend long hours working and is likely to limit their time available to other works. Third, our analysis considers attributes of only the decision maker. However, there are theories that suggest individuals' labor decision also depends on attributes of other household members. It is difficult to control for in case of rural Ethiopia where there are variety of household types (such as monogamous/polygamous households, households with children and several adults, households with absentee head or spouse). It will be very complicated to jointly model labor supply decisions of members within a household and test for interdependence.

Finally, since the analysis is done on a pooled cross-sectional data, the estimated effects should be considered as associations as opposed to causal effects. Further econometric analysis is required in order to make inferences as to the causal effects of the individual and household characteristics.

Attention should be given to the nonfarm sector given the fact that it mostly employees vulnerable groups (such as women, youth, and the land poor) that need to supplement meager production on subsistence agriculture. Besides, Ethiopia would benefit from pursuing and intensifying its efforts to ensure better access to education because, as this study and others show, better educated individuals are likely to prefer to work outside agriculture, participate more and for longer hours in nonagricultural activities. Most importantly, policies that aim at improving the efficiency of labor allocation in rural areas should take into consideration the difference in response to various factors that affect the decisions of male and female members of farm households.

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Appendix

Table A1: Summary statistics on the restricted sample of adults (N=10350)

Variable name	Definition	Mean	Std. Dev.	Min	Max
Dependent variables					
Agr_hours	Hours spent in any agricultural activity during the last seven days	14.51	17.5	0	98
Nonagr_hours	Hours spent in any nonagricultural activity during the last seven days	2.52	9.02	0	98
Total_hours	Hours spent in any rural activity during the last seven days	19.10	21.92	0	176
Explanatory Variables					
Individual characteristics					
Female	Gender of individual (=1 if female; =0 if male)	0.51	0.5	0	1
Age	Age of individual	35.54	12.14	15	65
Educ_status	Literacy (=1 if individual can read and write)	0.45	0.5	0	1
Schooling	Years of schooling of the individual	4.75	3.17	0	15
Household composition and wealth indicators					
No of child<6yrs	No of children under age 6 (infants)	0.74	0.91	0	5
No of child7-15yrs	No of children aged 6-14 (teenagers)	1.85	1.33	0	7
No of adult 15-65yrs	No of adult members aged 15-65	3.22	1.43	0	10
Household wealth indicators					
Landholding	Measured in hectares	0.51	1.09	0	15.15
Livestock holding	Measured in tropical livestock unit	1.06	2.13	0	26.6
Nonlabor_income	Non-labor income (unearned income)	2888.6	6096.4	0	42000
Shock occurrence					
Covariate_shock	(=1 if household faced covariate shocks such as flood, drought and landslides in last 12 months)	0.19	0.39	0	1
Instruments					
Avg_temp_wet_qrt	Mean temperature of the wettest quarter (°C)	177.98	30.36	103	319
Extension_program	(=1 if household has access to agricultural extension service)	0.16	0.37	0	1

- *The data source is LSMS-ISA (2010/11-2014/15) considering only adult members (15-65 years) of rural households.*
- *Survey weights are used when calculating mean and standard deviation.*
- *Weighted mean hours is computed for the whole sample, including zero hours reported.*
- *Weighted average years of schooling is computed for the literate group. Similarly, the average non-labor income is computed for the sub-sample of households that report to have received such income (8 percent).*

Figure A1: Histogram for hours of nonagricultural work for participants (untransformed)

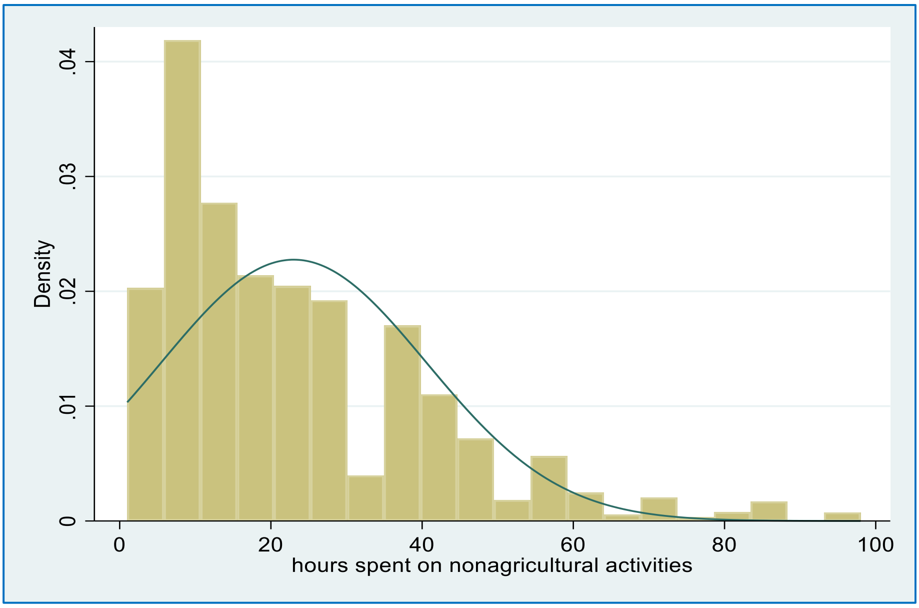

Figure A2: Histogram for logarithm hours of nonagricultural work (log transformation)

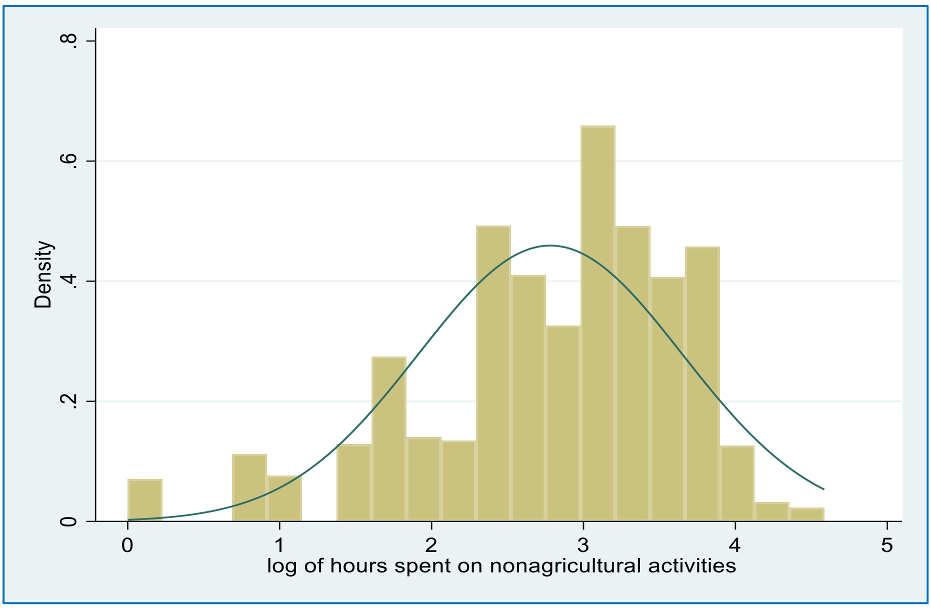

Figure A3: Histogram for square root of hours of nonagricultural work (square root transformation)

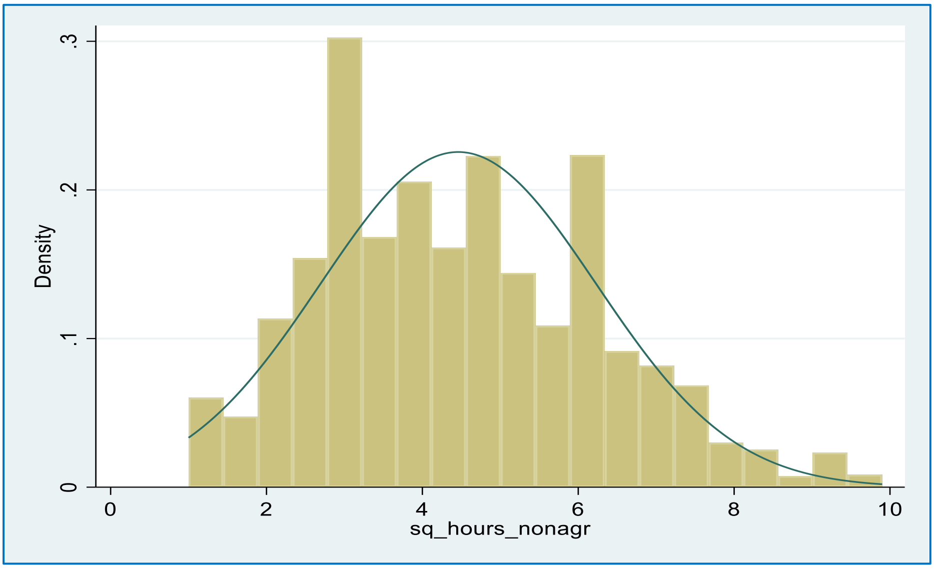

Figure A4. Kernel density plot of residual

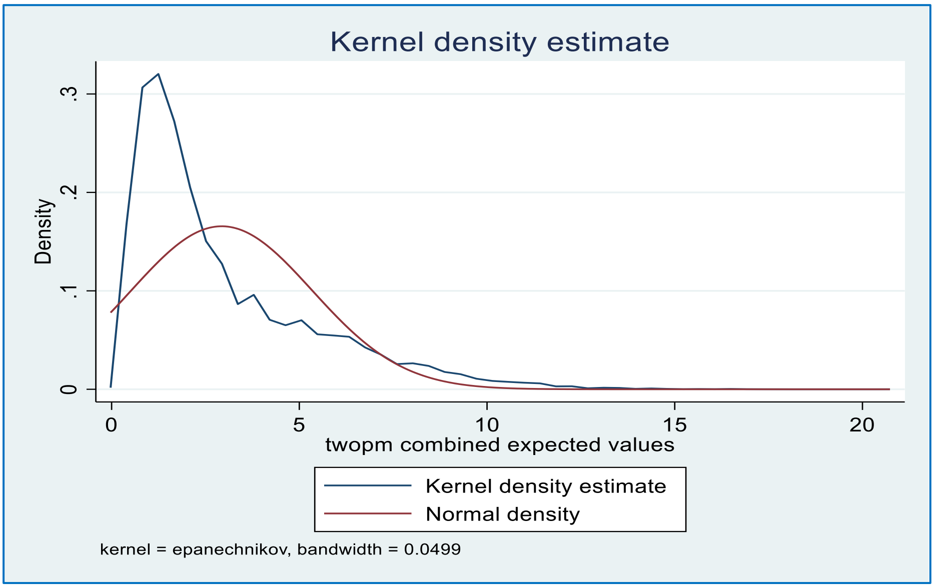

Figure A5. Gender differentials in hours of nonagricultural work

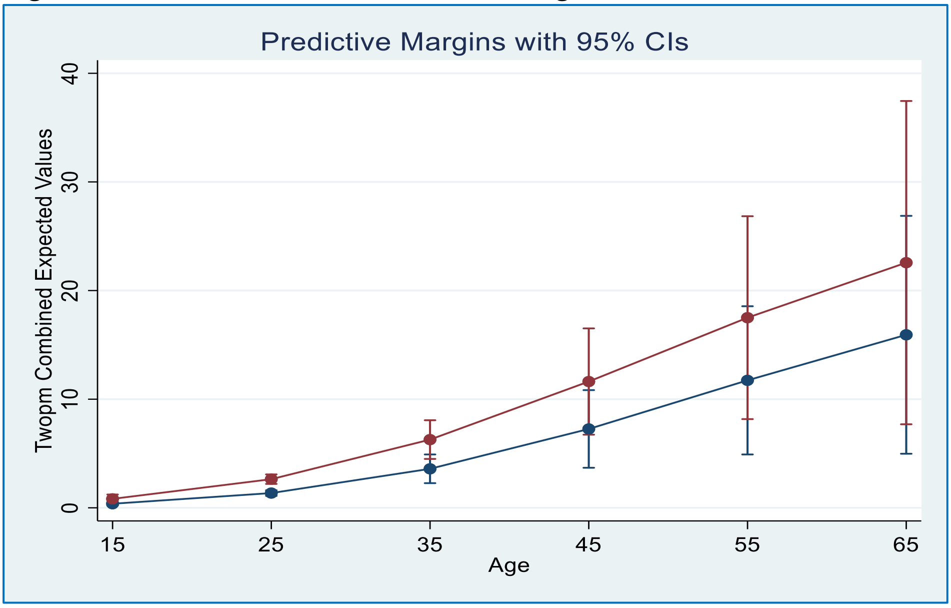

Figure A6. Age and predicted hours of nonagricultural work