

Essays on the Rural Labor Market: Evidence from Ethiopia

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LIST OF ABBREVIATIONS AND ACRONYMS

AAU	Addis Ababa University
AHA	Agricultural Household Model
APE	Average Partial Effect
ATT	Average Treatment Effect on the Treated
ATU	Average Treatment Effect on the Untreated
CFA	Control Function Approach
C4ED	Center for Evaluation and Development
CRE	Correlated Random Effects
CSA	Central Statistics Agency of Ethiopia
DAAD	German Academic Exchange Service
EA	Enumeration Area
EJDR	Ethiopian Journal of Development Research
EJE	Ethiopian Journal of Economics
ESR	Endogenous Switching Regression
ERSS	Ethiopian Rural Socio-Economic Survey
ESS	Ethiopian Socio-Economic Survey
ETB	Ethiopian currency
FE	Fixed Effects
GAGE	Grade-for-Age
GLM	Generalized Linear Model
Ha	Hectares
ICC	Intra-Class Correlation
ILO	International Labor Organization
IMR	Inverse Mills Ratio
IV	Instrumental Variable
JIBS	Jönköping International Business School
KMs	Kilometers
LR	Likelihood Ratio
LSMS-ISA	Living Standards Measurement Study – Integrated Surveys on Agriculture
NPC	National Planning Commission
OLS	Ordinary Least Squares

PSM	Propensity Score Matching
PSNP	Productive Safety Net Program
PSUs	Primary Sampling Units
RNFE	Rural Non-Farm Employment
SD	Standard Deviation
SE	Standard Error
SIDA	Swedish International Development Cooperation
SNSF	Swiss National Science Foundation
TLU	Tropical Livestock Unit
TPM	Two-Part Model
UN	United Nations
UNICEF	United Nations Children's Fund
US\$	United States Dollars
WB	World Bank

CHAPTER ONE

INTRODUCTION AND SUMMARY OF THE THESIS

This chapter introduces topic of the dissertation and provides an overview of the labor allocation discourse specific to rural Ethiopia. It justifies the need for research on rural labor market issues in a developing country context by defining research problems and identifying research gaps based on a brief review of prior work related to the problem. Then, the general objective and specific objectives are clearly defined. This is followed by a discussion of nature and suitability of the data used for the research that follow in subsequent chapters. Also discussed is a theoretical framework that can be applied to model rural labor markets in a developing country context. Towards the end, this chapter provides a summary of all the research papers included in the dissertation.

1.1. Background

Ethiopia's commitment towards economic growth and development is evidenced by various successful strategies implemented since the mid-1990s. These development strategies contributed to the notably robust growth in the country, which further translated into higher levels of well-being and considerable poverty reduction. Between 2011 and 2016, the country has maintained an average annual growth rate of over nine percent whereas the share of population living below national poverty line decreased from 30 percent to 24 percent (World Bank, 2020). Nonetheless, the country faces key challenges to sustain growth and accelerate poverty reduction. The challenges emanate from the ongoing transformations in the country, namely the rapid population growth, urbanization and the slow structural transformation.

Being home to more than 112 million people, Ethiopia is the second most populous African country after Nigeria (United Nations, 2019). The country faces one of the highest working-age population growth in the world, growing by more than 3.6 per cent per year over the past decade (that is, the working age population has grown by almost 2 million

per year) (Sarkar, 2019). In this regard, Ethiopia faces the critical challenge of creating enough jobs (about 2.8 million jobs per year) for the rapidly growing labor force (World Bank, 2017; Sarkar, 2019).

Furthermore, structural transformation seems to be taking place at a slow pace, significantly limiting the ability to absorb new entrants into the labor market. The Ethiopian economy is still considered as an agrarian economy, with more than three-quarters of the country's population engaged in agricultural activities such as crop production and livestock husbandry (Schmidt and Bekele, 2016; Sarkar, 2019).

Although still of central importance, agriculture is increasingly unable to provide a sufficient means of survival on its own. This challenge is daunting, particularly in rural areas where there is rapidly increasing workforce in the face of fragmented and declining landholdings (Bezu and Holden, 2014; Komikouma, Tnsue, and Kaiyu, 2021; Van Den Berg and Kumbi, 2006). The agriculture sector in Ethiopia is overwhelmingly dominated by small-scale farmers who cultivate less than 0.5 hectares by employing rudimentary tools and traditional low-tech farming techniques (Diriba, 2020; National Planning Commission, 2016). Besides, agriculture in Ethiopia is primarily rain-fed; thus it has been challenged by recurrent climate shocks (Etea et al., 2020; Weldegebriel, 2017; World Bank, 2017).

Considerable number of individuals and households in rural Ethiopia have been diversifying into employment in non-agricultural activities driven by both push and pull factors (Etea et al., 2020; Weldegebriel, 2017; Van den Broeck and Kilic, 2019). Numerous studies claim that non-farm employment diversification in rural Ethiopia is mainly driven by necessity in response to push factors such as lack of land and agricultural productive assets, land degradation, low agricultural productivity, risks and shocks in the face of missing markets (Bezu and Holden, 2014; Fentahun, Sani, and Kemaw, 2018; Komikouma et al., 2021; Tadele, 2021; World Bank, 2017).

As agricultural resources of farm households in rural Ethiopia are too limited to allow efficient use of household labor, household members engage in activities outside of agriculture. Non-farm wage employment, including casual work and Productive Safety Net

Program (PSNP) labor are important means of employment diversification in rural Ethiopia. However, the bulk of individuals who transitioned out of agriculture between 2012 and 2016 did so by taking up self-employment in the non-farm sector, mainly running a non-farm enterprise (World Bank, 2017). Most commonly, they engage in home-based non-agricultural businesses, selling of processed agricultural products and petty trading businesses that generate marginal income (CSA, 2017).

Non-farm employment is an important source of supplementary income which helps farm households to stabilize income, spread risks, improve consumption and sustain their livelihoods (Davis and Bezemer, 2004). However, non-farm employment opportunities remain scant and constrained in rural areas of Ethiopia (Bachewe, et al., 2016; Schmidt and Bekele, 2016). Most rural households participating in the non-farm activities were engaged in a low return business operation, probably due to low capacity in terms of education and wealth (Demie and Zeray, 2016).

Rural development and transformation require strengthening efforts that aim at improving the functioning of rural labor markets by inducing efficient labor allocation and promoting inclusive rural labor market. There is also a need for a comprehensive development plan that encourages successful livelihood diversification and enhances overall rural employment. The agricultural sector alone cannot be relied upon as the core activity for rural households and as a means of improving livelihoods in the study area. Increasing non-farm employment should be the objective of Ethiopia's development plan to bring about structural transformation. This calls for a paradigm shift in Ethiopia's approach to rural development, which has focused mainly on agricultural development as the way to address current challenges and achieve sustainable economic growth for rural households (Kassie, Kim, and Fellizar, 2017).

1.2. Statement of the problem

The rationale for any research on labor market issues in a developing country context departs from the recognition that, notwithstanding the increasing attention gained in recent years, empirical evidence on the subject remains scarce, both in itself and compared to other regions of the world. Empirical analysis for Africa, particularly Ethiopia, lags behind in this field of research while it is very likely to be one of the regions, if not the region, most in need.

Besides, there are some important research gaps and methodological shortcomings in the few existing studies on labor markets in Ethiopia. Most studies focus on urban areas, relatively neglecting rural labor markets where there is pervasive imperfections and inequalities (Krishnan, Selassie, and Dercon, 1998; Leavy and White, 2000; World Bank, 2007). Significant aspects of rural labor markets have not yet been researched, partly due to paucity of documented information in rural areas of developing countries. For instance, a survey of literature on Ethiopia shows that the focus has been on agriculture in terms of research; there is little empirical evidence regarding non-agricultural activities despite their crucial role as alternative source of productive employment for the rural workforce (Kassie et al., 2017; Kowalski et al., 2016). The non-farm sector is still not sufficiently researched despite its increasing importance.

The gap in the currently available empirical literature should be addressed by conducting additional studies that thoroughly investigate factors influencing individuals and households to engage in the non-farm sector. Furthermore, the role of the non-farm sector in rural development should be rigorously evaluated. It is also important to investigate the issue of intra-household allocation of work and the gender dimension in the labor allocation discourse as there is evidence of significant gender-based division of labor resulting from the prevailing norms about gender roles in the society (Yohannes, 2017).

The few available studies on rural markets in developing countries are often limited in geographical coverage, with their analysis based on data from a specific region or village, not being nationally representative (Block and Webb, 2001; Van Den Berg and Kumbi,

2006; Woldenhanna and Oskam, 2001). This limits their broader applicability given the wide heterogeneity within rural economies.

Another shortcoming is that most studies on Ethiopian labor markets rely on cross-sectional data that does not take into account a longer time horizon (Beyene, 2008; Etea et al., 2020; Schmidt and Bekele, 2016). Such cross-sectional data cannot be used to analyze behavior over a period of time or to establish cause-and-effect relationships. Besides, estimations based on such data may fail to yield statistically valid inference due to possible endogeneity problem resulting from omitted unobservables, heterogeneity and simultaneity biases (Wooldridge, 2002).

The current dissertation tries to bridge the identified gaps in the literature by synthesizing and providing empirical evidences on the conditions of rural labor market and the labor allocation discourse specific to rural Ethiopia. To this end, the dissertation incorporates studies that focus on the following important questions:

- What are the main factors that incentivize or impede labor allocation to rural non-agricultural activities among adult members of farm households?
- To what extent does participation and intensity of participation in rural non-agricultural activities vary between men and women? What drives such gender differences?
- Do rural farm households react to idiosyncratic and covariate shocks by increasing the intensity of child work in different rural activities? How does this depend on availability of other means of coping, such as non-labor income and credit?
- What is the implication of child labor on educational attainment of working children in rural areas?
- Does participation in non-farm activities in addition to farming contribute to improving welfare of households in rural Ethiopia? If so, what are the contributions, in terms of welfare gains/losses?

1.3. Objectives of the dissertation

The main concern of this dissertation is to deepen our understanding of the rural labor market and livelihood strategies in the context of Ethiopia. This is done by way of mapping labor time allocation across rural activities by gender and age profile. Then, the factors associated with labor allocation decisions are explored. Finally, the implications of labor allocation decisions and livelihood diversification choices are assessed.

Objectives of each of the three papers included in this dissertation can be summarized as follows:

- The first paper unveils and discusses factors which undoubtedly play important roles in determining the way people allocate their time across rural activities. Specifically, the study
 - identifies and discusses the major incentive and capacity factors influencing an individual's decision to participate in non-agricultural activities and the intensity of participation (hours of work time allocated by participants).
 - explores gender disparity in the allocation of time to non-farm activities.

- The second paper analyzes child labor in rural Ethiopia with a specific emphasis on idiosyncratic and covariate shocks as key determinants of child labor. It further investigates the implications of child labor on educational attainment. Specifically, the study
 - checks whether exposure to shocks increases households' reliance on child labor in the context of rural Ethiopia by examining the extent to which negative idiosyncratic and covariate shocks lead to greater intensity of child work in different rural activities.
 - empirically tests whether availability of coping strategies, such as household's non-labor income and credit access, help households ease the pressure to rely on child labor when hit by shocks.
 - evaluates effects of long working hours on educational attainment of school aged children.

- The third paper examines the role of rural non-farm employment (RNFE) in improving welfare of farm households in rural Ethiopia. Specifically, the study
 - looks into farm households' decision to diversify into RNFE and provide additional evidence on factors associated with RNFE participation.
 - evaluates the true causal impact of RNFE participation on welfare of farm households, measured by consumption expenditure.

Finally, this dissertation aims to suggest public policies, strategies and interventions that can induce efficient labor allocation, promote inclusive rural labor market, as well as improve rural livelihoods and welfare of children.

1.4. Justification and significance

The main concern and initiative of this thesis is to have a better understanding of the functioning of rural labor markets in the specific setting. This is crucial both from empirical and policy perspectives as it is well recognized that labor market plays a vital role in the development process. Efficient functioning of rural labor markets is important for rural development (Dillon, Brummund, and Mwabu, 2019).

Labor is a key resource factor of production in developing countries. As it is the primary endowment the poor households own in abundance, incomes from labor are a major determinant of welfare (Dillon, Brummund, and Mwabu, 2019; Bedemo, Getnet, and Kassa, 2013; Leavy and White, 2000). Hence, academics and policy makers must understand how and why households and individuals allocate this vital resource (labor) to different rural activities. A clear understanding of labor allocation behavior coupled with implications on households' welfare is of great importance for formulating policies.

This dissertation focuses on a specific context of Ethiopia in order to go more in depth in the analysis and to avoid overgeneralizations in the face of differing political and socio-economic characteristics across developing countries. Studying labor markets is of increasingly important for Ethiopia given the size of its growing population and the resulting in a large number of new entrants in the labor market year after year. Particularly, it is critical to know how the rural labor market behaves to better understand the rural

economy. As is the case in most developing countries, the Ethiopian rural labor market continues to be characterized by structural impediments and imperfections due to transaction costs and rigidities; which prevent optimal allocation of labor and constrain rural development (Tocco, Davidova, and Bailey, 2012). Assessing and understanding the situation in the specific setting helps to make real advances towards the ultimate goal of efficiency and rural development.

This dissertation provides relevant empirical proof to inspire evidence-based, targeted and gender-sensitive policy making. The findings of studies included in this dissertation offer useful insights to design policies and interventions intended to improve employment prospects, induce efficient labor allocation, and promote efficient and inclusive labor market in the rural domain. And such endeavor leads to efficiently functioning labor markets that help to improve rural livelihoods and bring about rural transformation.

1.5. The Data

All three papers in this dissertation draw on data from Ethiopian Socioeconomic Survey (ESS). The data is collected under the Living Standards Measurement Study-Integrated Surveys on Agriculture Initiative (LSMS-ISA), by the World Bank Group in collaboration with Ethiopian Central Statistical Authority (CSA).

The ESS started out as Ethiopian Rural Socioeconomic Survey (ERSS) in 2011/2012, with data collected from 3,969 households in rural area and small towns. The same households were re-interviewed in the subsequent two waves conducted in 2013/14 and 2015/16, along with an additional 1,500 households in urban areas (CSA, 2017).

Samples were drawn from the population in a two-stage stratified probability sample design. In the first stage, primary sampling units/ Enumeration Areas (EAs) were selected in each region, based on probabilities proportional to their sizes. Then in the second stage, individual households within these EAs are sampled. For the rural sample, a total of 12 households were randomly selected from each EA, of which 10 were randomly drawn from the sample of 30 agricultural households and two were randomly drawn from non-agricultural households (CSA, 2017).

Although the first round ESS data was not nationally representative, the subsequent rounds were representative at the national, urban/rural, and regional level, with the sample including households from all regions and covering a wide range of Ethiopian agro-ecosystems. In the interest of using the three-wave panel and to ensure comparability and soundness of the empirical analysis, we exclude urban households and focus on the rural sub-sample.

The first paper in this dissertation draws on cross-sectional data pooled from three waves of the ERSS data and a sample is constructed consisting of individual household members aged 15-64, which is in line with the conventional working-age range. On the other hand, the analysis for the second and third papers are based on a panel dataset constructed consisting of the three waves of the ERSS data. For the second paper, we construct a panel data set that consists of rural households with children aged 7-17 years in line with the child labor literature from developing countries. Lastly, the panel data set for the third paper consists of all rural households throughout the panel rounds.

The ESS data is very helpful to overcome some of the challenges associated with conducting empirical research on many developing countries where nationally representative and comprehensive data on time allocation are really scarce. The ESS surveys include extensive multi-topic questionnaire modules on households' characteristics, post-planting and post-harvest agriculture activities, and livestock, as well as services and infrastructure at a community or enumeration area (EA) level.

Each year's data were collected in three rounds of visits to the households. The first round was carried out in September and October and collected information on post-planting agriculture activities. The second round was conducted in November-December to complete the livestock questionnaire. Information on post-harvest agriculture and household characteristics were collected during the third round that took place from February-April.

The data is well-suited to labor market analysis as the surveys solicited sufficiently detailed information on households' demographics and other characteristics, shocks faced, assets

owned, job characteristics, non-farm enterprises in which households were involved, as well as access to services and infrastructure at community level. Moreover, the data enables analysis on implications of different choices made by providing information on multiple dimensions of wellbeing, including health, wealth, and education, as well as data on food and non-food consumption expenditure and food security, among others.

Interestingly, the ESS survey data is geo-referenced at EA level and this enables linking the household data with geographic data sets including climatic variables such as rainfall and temperature.

Particularly important for our analysis are that the data are collected at the individual-level and that the ESS survey is designed to track the sampled households and individuals over time. The longitudinal nature of the data allows us to test and control for unobservable variables that may bias cross-sectional analysis results.

1.6. Theoretical Framework: Non-separable Agricultural Household Model

The discussions in all the papers in this thesis are theoretically grounded on a modified agricultural household model suggested by Singh et al. (1986). The analysis are based on a *Non-separable Agricultural Household Model (AHM)*, which refers to the situation where the production, consumption, and work related decisions are brought into a single framework (Singh et al., 1986).

The non-separable AHM is considered to be appropriate in the context of rural areas of developing economies that are dominated by subsistence agriculture and where family labor is the major form of employment. Most rural households engage in agricultural production mainly for home consumption while only few practice semi-commercial agriculture using both self-sourced inputs (such as own labor and land) and some purchased inputs (such as seed, fertilizer, and pesticide). In this case, part of the products is used for households' own consumption and some are offered for sale in the market. Hence, decisions on labor, production and consumption are made simultaneously.

Besides, farm households in rural areas typically find themselves in a context of multiple market imperfections leading to non-separability of consumption and production decisions landholdings (Woldenhanna and Oskam, 2001; Van Den Berg and Kumbi, 2006). Furthermore, rural activities are susceptible to risks linked to weather variability and seasonality (Reardon, 1997). And risk explains the division of labor between different activities in rural areas, both within agriculture and between agricultural and non-farm activities while the division of labor within the household is mostly based on social norms, customs, and religion in the society. Also, production decisions are much influenced by a host of socio-demographic, economic, and institutional determinants (Sadoulet, De Janvry, and Benjamin, 1998).

The non-separable AHM is helpful to illustrate the direct and/or indirect welfare effects of rural households' labor allocation decisions which depend on the functioning of the market (Sadoulet, De Janvry, and Benjamin, 1998). For instance, the model is helpful to illustrate the ways in which increased income from rural non-farm employment (RNFE) can influence production and consumption in households facing resource constraints and imperfect markets.

While individual members of a household are considered as a unit of analysis in the first paper, the analysis in Paper 2 and 3 are done at household level based on the unitary model. The unitary model considers the household as a single decision-making unit and assumes that utility is based on one set of preferences for a household.

A typical farm household from a developing country is normally assumed to maximize a well-behaved quasi-concave, continuous and non-decreasing utility function described by:

$$U(C, L_l; Z_u) \tag{1.1}$$

Utility (U) is derived from consumption of various goods and leisure. C is a vector of consumption goods that consists of agricultural goods produced in the household farm (C_{hh}) and commodities purchased from the markets (C_{mkt}); L_l is leisure, and Z_u represents exogenous utility shifters, such as heterogeneous household characteristics. These factors are assumed to be exogenous to current household consumption decisions.

And a rural farm household's production occurs in accordance with the following well-behaved quasi-convex production technology:

$$Q = Q(L_a, X_v, K, A; Z_Q) \quad (1.2)$$

The household is assumed to produce agricultural products (Q) using labor dedicated to agricultural work (L_a); purchased variable inputs including hired labor (X_v); quasi-fixed factors (K) such as capital and fixed assets (A) such as land. Z_Q represents exogenous production shifters.

Labor use in agriculture includes both family labor and hired labor, which are assumed to be perfect substitutes in case of perfectly functioning labor market. But, in case of imperfect labor markets observed in many developing countries, family and hired labor may be imperfect substitutes in agricultural production. A farm household may not be able to easily replace family members with high farming skills who engage in non-farm work without incurring high transaction costs including costs of search and monitoring (Sadoulet, De Janvry, and Benjamin, 1998).

Rural households face the usual budget constraint given by:

$$C \leq p_a Q - p_v X_v + wL_{na} + R \quad (1.3)$$

Equation (1.3) states that a household's expenditure on the consumed commodities (C) must not exceed the monetary income from various activities. Net agricultural income is given by ($p_a Q - p_v X_v$) where p_a refers to price of agricultural outputs, p_v refers to price of market-purchased agricultural inputs such as fertilizer. The non-agricultural income is given by (wL_{na}) where w denotes the market wage rate. R refers to the unearned non-labor income including own exogenous income (e.g. subsidies and transfers) and savings.

It is also necessary to consider the fact that farm households in rural Ethiopia face liquidity constraint. If credit is not available on terms acceptable to the household, expenditures on inputs prior to harvest (including hired labor, if available) ($p_v X_v$) cannot exceed cash received from non-farm work (wL_{na}) plus non-labor income (R). i.e. $p_v X_v \leq wL_{na} + R$

Leaving out hired labor, which is included in purchased inputs, farm households also face labor time constraint described as follows:

$$L_a + L_{na} + L_l \leq \bar{L} \quad (1.4)$$

Equation (1.4) states that the sum of labor time allocated to agricultural production (L_a), non-agricultural work (L_{na}) and leisure time (L_l) should not exceed households' labor endowment (\bar{L}).

The conditions for optimal allocation of labor and consumption levels are obtained by maximizing utility subject to the given resource constraints on productivity, income and time as defined by Equations (1.2), (1.3) and (1.4) respectively. This requires forming the following Lagrange function:

$$\mathcal{L} = U(C, L_l; Z_U) - \lambda_1 [C + p_v X_v - p_a Q(L_a, X_v, K, A; Z_Q) - wL_{na} - R] - \lambda_2 (L_a + L_{na} + L_l - \bar{L}) \quad (1.5)$$

λ_1 and λ_2 are Lagrange multipliers for marginal utilities of income and time, respectively. Including these constraints in the Lagrangian equation does not imply that the constraints necessarily bind. If a constraint is not binding, the multiplier on that constraint will be zero.

The first-order conditions of Lagrange function given by Equations (1.6) and (1.7) are set assuming positive optimal hours of leisure time and agricultural work time. However, as indicated by Equation (1.8), farm households are not always assumed to allocate positive hours to non-agricultural works.

$$\frac{\partial \mathcal{L}}{\partial L_l} = \frac{\partial U}{\partial L_l} - \lambda_2 = 0; \quad L_l > 0 \quad (1.6)$$

$$\frac{\partial \mathcal{L}}{\partial L_a} = \lambda_1 p_a \frac{\partial Q}{\partial L_a} - \lambda_2 = 0; \quad L_a > 0 \quad (1.7)$$

$$\frac{\partial \mathcal{L}}{\partial L_{na}} = \lambda_1 w - \lambda_2 \geq 0; \quad L_{na} \geq 0; \quad L_{na} (\lambda_1 w - \lambda_2) = 0 \quad (1.8)$$

$$\frac{\partial \mathcal{L}}{\partial \lambda_2} = L_a + L_{na} + L_l - \bar{L} = 0 \quad (1.9)$$

Then, optimal values are determined by simultaneously solving the above first-order conditions. According to Singh et al. (1986), this is how the determination of labor allocation between different rural activities and demand of leisure is done based on the constrained optimization process.

1.7. Summary and contribution of each paper in the dissertation

This dissertation is organized into five chapters. The first chapter introduces the topic of the dissertation. It provides a background to the research problem, discusses the rationale for studying the particular research problem, and outlines the key contributions of the dissertation. This is followed by three independent article-based chapters on issues of labor market in rural Ethiopia. These chapters contain three single authored original research studies that have been written as papers for peer-reviewed publication. The first and second papers have already been accepted for publication in the Ethiopian Journal of Development Research (EJDR) and the Ethiopian Journal of Economics (EJE), respectively. The final chapter summarizes the key findings of the research and limitations, concludes and recommends based on the findings, and suggests direction for future research.

This section presents a summary of the three self-contained research studies, which are focal parts of this dissertation. For each of the studies, I highlight the specific objectives, methods employed, and major findings and elaborate on key contributions to existing literature. This dissertation adds a modest but concrete contribution to the insufficient research community's efforts to understand the functioning of rural labor markets. It does so by providing a synthesis of recent empirical evidence on the following issues in the context of rural Ethiopia:

Paper 1:

Labor allocation to Non-farm Activities in Rural Ethiopia: A Gender Perspective

This paper aims to identify major gender-specific incentive and capacity factors that influence labor allocation decisions and livelihood diversification strategies in rural Ethiopia. Specifically, the study examines factors that influence an individual's decision to participate or not to participate in a given rural non-farm activity, as well as the extent of participation (hours of non-farm work time allocated by participants in the activity). Moreover, the study probes possible gender disparity by checking the extent to which non-farm work participation and hours of work vary between adult male and female members of rural farm households.

The paper contributes to the literature by using data pooled from three waves of Ethiopian Rural Socioeconomic Survey (ERSS) (2011/12, 2013/14, 2015/16). The rich data helps to fill a lacuna in the existing empirical literature in two ways. First, it enables to analyze labor allocation decisions both at the extensive and intensive margins. Second, it allows to study the heterogeneity of main results by disaggregating the study sample into different subsets. In this regard, this study examines variations of the main results related to labor allocation decisions by gender of adult members of farm households in rural Ethiopia.

The analysis is done using a Two-Part Model (TPM), which allows joint modeling of the participation and the intensity of participation decisions. Besides, the Control Function Approach (CFA) is used to account for the effect of farm work hours on the decision to allocate labor to non-farm activities, controlling for simultaneity bias that may result from the interdependence and trade-off of work decisions. This is important because labor allocation to a specific rural activity may actually not represent a separate decision, rather it is outcome of an optimization process in which allocation of time to different activities are jointly determined.

The results based on both descriptive methods and quantitative (regression models) reveal that adult members of farm households are decided to engage in non-farm activities due to pull and push factors. Involvements in rural non-farm activities are mainly influenced by individual attributes and household characteristics. Also, capacity factors such as education, land size, livestock holdings and non-labor income have important roles in adults' involvements non-farm activities.

The research hints that women, youth, and the land-poor engage more in non-farm activities. More importantly, the study reveals that there is gender disparity in labor allocations in rural Ethiopia. Female members of farm households are more likely to participate in non-farm works, and when they do, they also work more hours than males. However, female members of a farm household with many infants are less likely to engage in non-agricultural works and if engaged work relatively shorter hours. Besides, there is difference in response to the factors associated with labor allocation decisions of men and

women. For instance, non-labor income is found to increase the probability of participation in non-agricultural activities, but only for female members of farm households.

Paper 2:

Heterogeneous Impact of Shocks on Child Time Allocation: Evidence from Rural Ethiopia

This paper aims to determine whether there is empirical evidence for the commonly made assumption that exposure to idiosyncratic shocks (such as crop damage, illness, or death of family member) and covariate shocks (such as flood, drought, heavy rain, and landslides) increases the intensity of child work (that is, number of hours children spend on economic activities as well as domestic chores). Specifically, we empirically test to what extent rural households use child labor as a buffer stock and how this depends on availability of other coping strategies. Finally, we examine the probable adverse effect of excessive hours of child work on educational attainment of school aged children in rural Ethiopia.

The analysis in this paper is based on an appropriate empirical methodology that accounts for a number of empirical issues, including endogeneity, the nested nature of the data, the multilevel feature of the child outcomes, and the fact that the child outcome measures (hours of work and the measure of educational attainment) are left-censored. Child work is analyzed at the intensive margin using multilevel mixed effects tobit model based on a balanced panel data constructed from the three waves of Ethiopian Rural Socioeconomic Survey (ERSS) (2011/12, 2013/14, 2015/16). The panel structure of the data enables us to test and control for unobservable effects that may bias cross-sectional results. It also helps to exploit the dynamics in child work and educational attainment, conditional on other relevant covariates.

The research findings support the contention confirm the claim that shocks induce child labor. This paper recognizes the fact that child labor does not always work through the commonly assumed channel of deterring school enrolment. The focus of the child labor discourse is being shifted from its interaction with school enrolment to that with educational attainment. In this regard, there is a strong statistical evidence on the adverse effect of excessive hours of child work on educational attainment, as measured by the age-adjusted school outcome variable – grade for age (GAGE). That is, child labor exhibits a

negative and heterogenous effect on children's educational attainment, with stronger effect for young children under 12 years.

The study provides empirical evidence on the heterogeneous effect of shocks. There is a significant increase in children's time spent on economic activities (agricultural and non-agricultural activities) in response to idiosyncratic shocks. On the other hand, covariate shocks lead to an increase in total hours of child work including household activities (fetching water and firewood).

Results from gender disaggregated analysis infer asymmetries in the effects of shocks, probably resulting from the observed gender-based differences in the allocation of time. There is gender bias in child labor when households face shocks; only girls seem to experience harmful effects from both idiosyncratic and covariate shocks, in terms of increased hours of work.

Access to finance helps households to lessen the pressure to rely on child labor when hit by covariate shock although it is found to increase hours of child work both at normal times and when households are hit by idiosyncratic shocks. But, according to results from the age disaggregated analysis, credit access serves as a buffer against idiosyncratic shocks for children aged 12-14 years. It also buffers against covariate shocks for adolescents (14-17 years). Similarly, non-labor income has a buffering effect against idiosyncratic shocks on child labor hours for boys, but not for girls.

This paper contributes to the literature in several ways. First and foremost, the research is highly relevant given the prevalence of the child labor problem in most rural areas where the consequences of shocks are pronounced. The paper contributes to the literature by examining the drivers of child labor and the consequences in educational attainment of children in rural Ethiopia. The findings from such empirical studies are quite helpful to pinpoint potentially important determinants of child labor and thereby, point at mechanisms that can be used to tackle it. Moreover, a better understanding of the inefficiency and trade-of between child labor and educational attainment is essential to formulate policies aimed at curbing child labor and its repercussions.

The study makes use of the rich ERSS data to scrutinize the heterogeneous impact of shocks as different categories of shocks may not equally affect hours of child work in different activities. Precisely, the research makes a thorough investigation to grasp the direction and magnitude of the effect of different types of shocks (idiosyncratic and covariate shocks) on hours of child work spent in different rural activities (economic and household activities including domestic chores).

The sample is disaggregated based on gender and age of the child, as well as other household features such as access to credit and non-labor income. Introducing heterogeneity in the analysis of effects of shocks may help to identify vulnerable groups which should be targeted when devising strategies to address the child labor problem in the study settings.

Also, this research complements current efforts in the literature that focus on implications of coping mechanisms (such as access to credit and insurance mechanisms) in mitigating the impact of shocks on child vulnerability in the context of a rural subsistence economy.

Paper 3:

Does Rural Non-farm Employment Diversification Improve Household Welfare?

This paper investigates farm households' decision to diversify into rural non-farm employment (RNFE) and evaluates the effect of such endeavor in terms of improving welfare in rural Ethiopia. The major premise of this study is that RNFE is an important factor affecting household welfare. This premise is tested using a balanced panel data from three waves of Ethiopian Rural Socioeconomic Survey (2011/12, 2013/14, 2015/16). The study adopts an Endogenous Switching Regression (ESR) model to evaluate the true causal impact of RNFE on welfare of farm households in rural Ethiopia. The ESR model is estimated on correlated random effects (CRE) framework, by using the Mundlak–Chamberlain device with household-level time averages as additional controls.

The estimation results indicate that household welfare (proxied by household consumption) is influenced by RNFE participation as well as other household features (such as gender and age of the head of household, household size measured by labor endowment and

dependency ratio, land size, access to credit, and distance to the nearest market). The results also suggest that RNFE helps to increase consumption of farm households participating in non-farm activities and hence improves welfare of farm households the study setting. RNFE participant households make a positive, albeit small, consumption gain (ETB 230 (US\$ 8.05) worth of consumption per year) from participating in non-farm activities, even after controlling for all confounding factors. On the contrary, non-participating households would lose ETB 140 (US\$ 4.90) worth of consumption per year on average by participating in rural non-farm activities, given their characteristics and circumstances. It is rational for the typical non-participating household not to participate in RNFE as there are no expected positive consumption gains from engaging in non-farm activities among the households who do not currently choose to do so.

This study complements existing studies on rural employment in two ways. First, the paper contributes to the literature on employment diversification by providing additional evidence on the pull and push factors influencing participation in non-farm activities in rural Ethiopia. Moreover, the study provides key improvements in terms of causal interpretations of the relationship between participation in non-farm activities and the welfare outcome variable (consumption expenditure). This is done by using an appropriate econometric approach that better addresses potentially endogenous selection of households into non-farm income generating activities. Precisely, we use an Endogenous Switching Regression (ESR) model. This model is appropriate as it helps to reduce the bias and inconsistency of the estimations by controlling for selection bias due to observed and unobserved characteristics of households and systematic differences between participants and non-participants of non-farm income generating activities.

Estimation of the two-stage ESR is done on correlated random effects (CRE) framework, by using the Mundlak–Chamberlain device with household-level time averages as additional controls, controlling for unobserved or time-invariant observable households characteristics that may correlate with RNFE participation decisions. This helps to effectively deal with time-invariant heterogeneity and address endogeneity rooted in measurement errors and simultaneous relationships. The use of these empirical methods with panel data makes the estimations more robust and less prone to endogeneity problems.

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CHAPTER TWO

LABOR ALLOCATION TO NON-FARM ACTIVITIES IN RURAL ETHIOPIA: A GENDER PERSPECTIVE

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 both at the extensive and intensive margins using a Two-Parts 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 holdings and non-labor income. Besides, the results suggest gender disparity in the allocation of labor to non-agricultural activities in rural Ethiopia. Female members of farm households are more likely to participate in non-agricultural works, and when they do, they also work more hours than male members. Also, gender differences are observed in some factors that affect labor allocation decisions such as education, number of infants in a household and non-labor income. 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, Non-agricultural activities, Two-Parts Model, Rural Ethiopia

JEL Codes: D13, J22, Q12

2.1. Introduction

Households and individuals in rural areas of developing countries do not limit labor allocation to agricultural activities (namely crop production, livestock rearing, horticulture, and fishery); but also involve in a variety of non-agricultural (non-farm) activities in secondary and tertiary sectors (Davis *et al.*, 2014; Ellis, 1998; Haggblade *et al.*, 2007; Loison, 2015; Nagler and Naudé, 2017; Reardon, 1997).

The current study endeavors to identify the major factors that determine the way people allocate their time in the context of rural Ethiopia. The focus is on non-farm activities given the growing importance of such activities in rural settings. This study analyzes the factors influencing the decision to participate in non-farm activities as well as the level of participation (hours of non-farm work) among adult members of farm households in rural Ethiopia. Also explored is the effect of gender on individual decisions to allocate labor to non-farm activities. The study questions whether men and women differ in their allocation of time to non-farm activities and examines to what extent non-farm work participation and hours of non-farm work vary by gender.

There is a growing literature that investigate factors behind labor allocation decisions in rural areas. Nevertheless, the issue of labor allocation to rural non-farm activities is not sufficiently covered in the case of developing countries and the few prior studies on the subject have several of limitations.

First, most studies, particularly those from Ethiopia, are conducted based on household surveys with limited coverage that hardly represent the whole country (see Amsalu, Getnet and Kassa, 2013; Van Den Berg and Kumbi, 2006; Woldenhanna and Oskam, 2001). Second, most studies limit their analysis at the extensive margin, where they only look at determinants of the decision to participate or not to participate in a given rural activity and fail to further look into the factors that influence the extent of participation (that is, the amount of time the participant allocates to the given rural activity) (Bezu and Barrett (2010). Third, previous studies fail to consider the fact that labor allocation to a specific rural activity may actually not represent a separate decision, rather is outcome of an optimization process in which allocation of time to different activities are jointly

determined. Fourth, findings from past studies on rural labor allocation are mixed and thus require further investigation for a more nuanced documentation of factors driving rural labor allocation decisions.

Fifth, prior studies mostly consider the household as their unit of analysis and fail to investigate intra-household differences in labor allocation decisions. For instance, the issue of gender differences in labor force participation and hours of work has been insufficiently treated in the literature. Empirical evidence in this regard remains scarce, especially for Ethiopia because of paucity of appropriate time use data. Only few studies attempt to look into gender issues using gender of the household head as a proxy for gender differences (Lemi, 2009; Bezu and Barrett, 2010). The drawback of such studies is that they do not distinguish between men and women within households. Moreover, they fail to recognize the inherent difference between male- and female-headed households in terms of observable as well as unobservable characteristics.

This study aims to help fill the gap in current knowledge and contribute to a better understanding of the labor allocation decisions in the context of rural Ethiopia using a nationally representative household survey data. Data is pooled from the first three rounds of Ethiopian Socio-economic Survey (ERSS) (2011/12, 2013/14 and 2015/16).

In this paper, we analyze labor allocation decisions of adult members of farm households both at the extensive as well as intensive margin using the Two-Parts Model (TPM). TPM decomposes the density of the outcome into a process that generates zero and another that generates positive values. It is an appropriate approach as it provides a more realistic model of the labor market by distinguishing the participation decision and the hours of work decision. The approach allows different mechanisms to determine the participation and hours of work decisions. Furthermore, the analysis in this paper acknowledges the potential interdependence of work decisions across alternative rural activities which may result in simultaneity bias. An attempt is made to properly address this concern using the Control Function Approach (CFA) which corrects for biases that arise due to endogeneity problems.

The rest of the paper is organized as follows. Section two briefly reviews the literature on the determinants of rural labor allocation and identifies the knowledge gap. Section three sets the theoretical framework which serves as a foundation for the empirical analysis relating to the time allocation decisions of farm household members. Section four specifies the empirical strategy for the analysis while section five describes the data and main variables of interest for the analysis. Section six presents the empirical results followed by some discussion. The last section summarizes the main findings and concludes.

2.2. Literature review

Conceptually, the decision to allocate labor to non-farm activities may be influenced by *incentives* offered and *capacity* factors (Davis and Bezemer, 2004). Incentives can be further categorized into *demand-pull* and *distress-push* factors.

“*Demand-pull*” factors refer to employment diversification that occurs as a deliberate strategy taking into account the earning difference between sectors and the associated riskiness. Demand-pull diversification takes place when returns to non-farm employment are higher or less risky than in agriculture (Reardon, 1997; Davis and Bezemer, 2004). Other incentives that motivate non-farm employment include the desire to accumulate wealth through the extra income generated from a non-farm activity and/or to take advantage of market and non-market opportunities in the rural non-farm economy (Barrett *et al.*, 2001; Ellis, 1998; Haggblade *et al.*, 2007).

Another set of motives comprise “*distress-push*” factors, where non-farm employment serves as an involuntarily strategy for survival in the struggle to overcome livelihood distress under deteriorating conditions (Barrett, *et al.*, 2001; Lanjouw and Lanjouw, 1995). The push factors are predominantly related to the poor performance of the agricultural sector in many developing countries (Haggblade *et al.*, 2007). In the specific case of rural Ethiopia, agriculture is unable to offer a sufficient means of livelihood and the agricultural resources of many farm households are too limited to allow for efficient use of household labor (Bezu and Barrett, 2010; Bezu and Holden, 2014; Tafesse *et al.*, 2015). Thus, individuals who are constrained by meager employment opportunities in the agricultural sector are often pushed to look for alternative employment in activities outside farming.

The main push factors in Ethiopia are land scarcity and fragmentation of farm plots driven by rapid population growth (Bezu and Holden, 2014; Schmidt and Bekele, 2016; Van den Berg and Kumbi, 2006). The Ethiopian agricultural sector can hardly sustain the pressure of abundant labor force on limited land resources; it has limited potential to productively absorb the additional workforce created by population growth, or even to retain the existing disguised labor force in the sector (Van den Berg and Kumbi, 2006). Furthermore, the agriculture sector in Ethiopia, as in most parts of the developing world, is characterized by smallholder farmers who produce on a subsistence level, using simple crude tools and traditional farming method. This has led to low agricultural productivity and the resulting low incomes (Bezu and Holden, 2014; Etea *et al.*, 2020; Holden *et al.*, 2004).

Employment diversification for 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 (Barrett *et al.*, 2001; Lanjouw and Lanjouw, 1995; 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 non-farm activities in order to self-insure themselves against risks (Barrett *et al.*, 2001; Haggblade *et al.*, 2007).

In addition to the push and pull factors, whether and to what extent farm households engage in non-farm activities also depends on *capacity* factors such as human and financial capital, as well as availability of infrastructure (Bezu and Barrett, 2010). Resource constraints related to such capacity factors become binding only where markets do not operate in a competitive way (Reardon, 1997).

Also, personal traits (such as age and gender) play an important role in determining participation in non-farm activities in rural areas of many developing countries including Ethiopia, where there is unequal access to markets and resources based on individual characters. Particularly, gender disparities in factors affecting participation in non-farm activities cannot be ignored as they often result from gender specific inequality in education and labor markets and in prevailing norms about the role of females and males in society.

Prior studies have identified individual capabilities, endowments (physical, human, natural capital), wealth and other household characteristics and institutional factors to play a role in driving engagement in different economic activities in rural areas of most developing countries. Regarding determinants of labor allocation to non-farm activity, factors that have featured prominently in many studies include gender, education, age, household size and composition, farm household's disposable income, distance to the nearest market, distance to a main road, access to credit, farming experience and shocks, among others (*e.g.*, Abdulai and Crole-Rees, 2001; Barrett et al., 2001; Babatunde, 2010; Ellis, 2000).

There are few studies from Ethiopia that try to look into labor allocation decisions in rural areas. Lemi (2010) studied the quite elastic labor allocation of rural households between on-farm tasks and off-farm employment in Ethiopia. Results of the study show 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. He also looked at factors that influence intensity of off-farm activity and showed that off-farm intensity increases with land size and decreases with livestock holding.

Woldenhanna and Oskam (2001) examined households' labor supply to non-farm employment and found upward sloping labor supply curves for both wage and self-employment. Moreover, they found that labor is negatively correlated with agricultural land, livestock, and non-labor income. According to their findings, households engage in wage employment due to push factors while they are pulled to self-employment to gain attractive returns.

Likewise, Bezu and Barrett (2010) analyzed rural non-farm employment choice of individuals in Ethiopia. The findings suggest that factors that influence individuals' decision to participate in non-farm employment differ for 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. Among set of incentives and capacity variables that affect participation in non-farm

employment, education is the most important. It positively influences participation in all types of non-farm employment.

Amsalu, Getnet and Kassa (2013) analyzed determinants of off-farm labor supply decision of adult male and female members of households in rural Western Ethiopia using two stage double hurdle process. According to the results, participation decisions are influenced by individual attributes, family composition variables, credit access, off-farm equipment, and location factors; while the hours of work decisions are mainly influenced by individual and household attributes, wage rates and location factors.

Recently, Schmidt and Bekele (2016) examined labor diversification in Ethiopia focusing on youth that have relatively greater probability of working in non-agricultural enterprises. Their analysis suggests that push factors are at play with regards to non-agricultural 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.

2.3. Theoretical framework

The analytical framework for the current study is based on a modified agricultural household model, where the production, consumption, and work-related decisions are brought into a single framework. The *non-separable model* suggested by Singh et al. (1986) is considered appropriate in the context of rural areas of developing economies where there are multiple market imperfections (such as lack of an insurance and credit markets) and production decisions are much influenced by a host of socio-demographic, economic, and institutional determinants (Sadoulet et al., 1998).

Previous studies often use the unitary model, where the unit of analysis is at household level with no attempt in differentiating which family member involves in non-farm activities. Such analysis has limitations when analyzing the causes and gains of gender differences since it assumes that utility is based on one set of preferences for a household. This study considers individual members of farm households as a unit of analysis since a household is composed of several decision makers who have different preferences.

Thus, the basic model is the one with an optimizing individual who maximizes utility (Equation 2.1) defined over leisure (T_l^i), consumption (C) and taste and preferences variables (I^i, H) subject to resource constraints for income and time illustrated by Equation (2.2) and Equation (2.3) respectively:

$$U(T_l^i, C ; I^i, H) \quad (2.1)$$

$$T^i = (T_a^i + T_{na}^i + T_l^i) \quad \text{with } T_{na}^i \geq 0 \quad (2.2)$$

$$Y = \pi(p_a, v_a, T_a^i, A ; I^i, H) + y_{na}T_{na}^i + R \quad (2.3)$$

where I^i and H are vectors of taste and preference variables. T^i denotes the fixed time available to individual i , with leisure time of T_l^i , and time allocated to agricultural and non-agricultural activities denoted by T_a^i and T_{na}^i respectively.

The household income (Y) is the sum of profit from agricultural production, non-agricultural income ($y_{na}T_{na}^i$), and non-labor income (unearned income)(R). The conditional profit function given by $\pi(p_a, v_a, T_a^i, A ; I^i, H)$ depends on price of agricultural output, variable input prices, agricultural labor of household members, other agricultural fixed inputs, individual attributes, and household characteristics.

The variables included after the semicolon in the utility function (I^i, H) are control variables representing individual and household attributes such as gender, age, education level, household size (number of children, labor endowment), and households' wealth indicators. These variables are included in the utility function to emphasize that labor allocation decision across rural activities depends on the endogenous relative marginal values of labor, which in turn are affected by vectors of individual and household characteristics.

The conceptual model dictates that labor is allocated across different rural activities to equate marginal utility of labor across alternative employment options, given price vector, budget constraint, and time endowment.

Given our focus on non-agricultural work, it is convenient to assume interior solution for all choices except non-agricultural work. Accordingly, under regular assumptions, the necessary conditions for the optimal allocation of labor to agricultural and non-agricultural activities are given by Equation (2.4) and Equation (2.5) respectively.

$$-\left(\frac{\partial U/\partial T_a^i}{\partial U/\partial Y}\right) = \frac{\partial \pi}{\partial T_j^i} \quad (2.4)$$

$$-\left(\frac{\partial U/\partial T_{na}^i}{\partial U/\partial Y}\right) - \left(\frac{\lambda}{\partial U/\partial Y}\right) = y_{na}^i \quad (2.5)$$

where λ denotes the Lagrange multiplier associated with positivity constraints on non-agricultural work. It refers to the discounted marginal value of labor invested in non-agricultural activity (shadow price of time allocated to non-agricultural work).

Equation (2.4) implies that marginal rate of substitution of agricultural labor for money income should be equated to the discounted marginal value of labor invested (shadow price of that labor time). And Equation (2.5) suggests that the marginal rate of substitution of non-agricultural work for income should equal the income offered in the labor market if an individual engages in non-agricultural work.

In fact, an individual decides to allocate labor to non-agricultural activities if the income offered for that work exceeds the marginal rate of substitution of non-agricultural work for income. In a perfect market system, individuals choose to engage in non-agricultural activity as long as marginal value of agricultural labor (the reservation wage)¹ is less than the income offered in non-agricultural sector (Singh et al., 1986). However, in case of imperfections, decisions are non-separable and are based on unobservable shadow prices rather than market prices. It is then the risk-discounted marginal value of labor invested across activities that determine the patterns of engagement of individuals in different rural activities (Sadoulet et al., 1998). And labor allocation is influenced by factors that affect

¹¹ The reservation wage is the lowest wage rate at which a worker would be willing to accept a particular type of job. An increase in the reservation wage would reduce the probability that an individual participates in the labor force.

relative values of investing labor in various activities. Variables that raise the income offered for non-agricultural work increase probability of non-agricultural work participation and time allocation, while variables that raise reservation wage have the opposite effect.

2.4. Empirical strategy: Two-Part Model (TPM)

The outcome variable of interest for this analysis, hours of non-agricultural work, is a semi-continuous variable with a mass point at zero and is smoothly distributed over strictly positive values. For this kind of distribution, the normality assumption does not hold. Thus, running linear regression models would give biased and inconsistent parameter estimates (Wooldridge, 2012). The conventional approach to deal with such data is to use a class of limited dependent-variable models or censored regression models (such as Tobit) or sample selection models (such as Heckman's two-stage estimator model) or double-hurdle models, also known as two-part models.

The standard Tobit model is a good starting point, but it is restrictive in interpreting the zero values as corner solutions in utility maximization. That is, zero observations refer to potential workers who are supposed to participate but chose not to work at the current level of economic incentives. The model ignores the zero observations due to respondents' non-participation decisions. Also, Tobit is restrictive assuming that the probability of participation and the level of participation (the actual hours of work for the participants) are determined by the same underlying process. In other words, the model assumes a single decision process for which non-participation is actual corner solution (Wooldridge, 2012).

There are alternative models that presume two interdependent decisions and allow different factors to influence the two decisions. The Heckman's sample selection model is a candidate in such a context, but it is restrictive assuming that none of the zero observations may be due to a corner solution (Heckman, 1974). The zeros in the Heckman's model denote censored values of the positive hours worked. The model only includes workers who chose positive hours of work and does not observe anything about the people who do

not work. Heckman's model is less suitable for analysis of hours worked in this paper since the zero values in the dependent variable (hours of non-agricultural work) are true zeros.

In modelling the sequential participation and intensity of participation decisions, Two-Part Model (TPM) is a more flexible alternative than the Tobit or Heckman models since it allows possibility of zero observations in the first and second hurdles (Cragg, 1971; Duan et al., 1984). The first hurdle determines whether the individual is zero types (do not participate in non-agricultural activity) and the second hurdle determines the extent of participating in non-agricultural activities given the individual is not zero types.

The TPM considers the fact that zero observations may arise due to behavior of respondents, deliberate choices, sampling errors, absenteeism, or random circumstances. Individuals may not prefer to work, may lack qualifications, or may work on some days but not others due to other commitments or illness (Salmon and Tanguye, 2015). 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). Moreover, TPM allows the inclusion of all observations in the sample; where we still observe those who do not work but record zero hours of work. Unlike Heckman's model, in this case there is no sample selection problem as there is no missing data.

TPM has been used to model labor supply decisions in developing countries. For instance, Matshe and Young (2004) applied TPM to model off-farm labor allocation Zimbabwe. Similarly, Ibrahim and Srinivasan (2013) used the double hurdle model to examine the off-farm labor supply decisions of rural households in Nigeria. Recently, Salmon and Tanguye (2015) employed the hurdle model to investigate the impact of electrification on male and female labor supply decisions within rural households in Nigeria.

In this paper, we employ Two-Parts Model (TPM) to analyze labor time allocation to non-agricultural activities in rural Ethiopia. The model fits our problem better as it allows the joint modeling of the decision to participate in non-agricultural activities and the intensity of participation (hours of work time allocated by participants). The approach allows different mechanisms to determine the participation and hours of work decisions. Besides,

factors that explain participation may not have the same effect on time allocation decision (Cragg, 1971; Duan et al., 1984).

TPM considers two separate decisions: *the participation decision* (whether to participate in the non-agricultural work) and *the level of participation* (the amount of time the participant allocates to non-agricultural work), conditional on participation being positive. In this model, a two-stage process must have been completed before a positive hour of work is observed: first, the individual has decided to participate in non-agricultural work; and second, this individual has allocated some amount of time to non-agricultural work.

The model can be written as follows:

$$p_i^* = z_i' \gamma + \varepsilon_i, \quad p_i = \begin{cases} 1 & \text{if } p_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \quad (2.6)$$

$$h_i^* = x_i' \beta + u_i, \quad h_i = \begin{cases} h_i^* & \text{if } h_i^* > 0 \text{ and } p_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \quad (2.7)$$

Equation (2.6) presents the first part (binary) which captures the likelihood of participation decision with a dummy variable that takes the value of one if individual i participates in any non-agricultural work during the reference period, and the value zero if no participation is recorded.

p_i^* is a latent variable associated with non-agricultural work participation and it represents the binary censoring, while p_i is the corresponding observed value.

Equation (2.7) presents the second part (continuous) that models the decision on the intensity of participation conditional on the participation decision, explicitly considering that the observed hours of non-agricultural work (h_i) is censored from below at zero. The actual observed hours of work (h_i) equals the unobserved latent value associated with potential hours of non-agricultural work (h_i^*) only when a positive hour of work is reported; otherwise, it takes the value of zero. This indicates that the observed hours of work (h_i) is zero either when there is censoring at zero or if there is faulty reporting, or due to some random circumstance.

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 unknown parameters; ε_i and u_i are the error terms.

TPM does not make any assumptions about correlation between errors from the two equations though they are commonly assumed to be independently distributed: $\varepsilon_i \sim N(0,1)$ and $u_i \sim N(0, \delta^2)$. Cragg's (1971) original model assumes independence between the participation decision and the structural equation, but this assumption was dropped in later applications (Blundell et al., 1987; Jones, 1989; Blundell et al., 1998). The two decisions (participation and intensity/hours of work) can also be estimated simultaneously by allowing correlation between error terms and assuming they are distributed as a bi-variate normal distribution:

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

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

$$L = \prod_{h=0} \left\{ 1 - \Phi_2 \left(z'_i \gamma, \frac{x'_i \beta}{\sigma_h}, \rho \right) \right\} \prod_{h>0} \left\{ \Phi_1 \left\{ \frac{z'_i \gamma + \frac{\rho}{\sigma_h} (h_i - x'_i \beta)}{\sqrt{1 - \rho^2}} \right\} \frac{1}{\sigma_h} \varnothing \left(\frac{h_i - x'_i \beta}{\sigma_h} \right) \right\} \quad (2.8)$$

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

2.5. Description of data and relevant variables

This paper uses pooled cross-sectional data of the Ethiopian Rural Socio-Economic Survey (ERSS) from the World Bank's Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA) database covering three rounds of biennial data over a time span of five years (2011/12, 2013/14, 2015/16). The database is the result of nationally representative, household-level panel data surveys and has a strong focus on agriculture and rural development.

The data has a section for time use² with details on how different individuals spend their time on different rural activities (collecting fuel wood, fetching water, working on agricultural activities, non-agricultural activities, temporary/casual work or salaried job, and unpaid apprentice). Thus, the data is helpful to map the allocation of labor time in rural Ethiopia and make precise analysis of the labor allocation decisions.

For our analysis, we used a restricted sample considering only adult members of households (aged between 15 and 65 years) that consists of 3,450 individuals observed in three waves, resulting in a pooled balanced sample of 10,350 adults. Table A_1 in the Appendix reports the summary statistics for the variables included in the analysis on the restricted sample. For the sake of parsimony, in what follows we provide details only for variables indicating labor allocation across rural activities.

The outcome variable for our analysis is the *hours of non-agricultural work* recorded for each individual sampled during the seven days preceding the survey. Non-agricultural 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 non-agricultural self-employment, wage employment and unpaid work.

² The time use data was collected during the post-harvest season for the major agricultural season in many parts of the country (January-May).

**Table 2.1: Labor allocation across rural activities in Ethiopia
(Summary statistics by survey round of ERSS)**

	Pooled sample (N=10,530)	Survey year		
		2011/12 (N=3,450)	2013/14 (N=3,450)	2015/16 (N=3,450)
<i>Incidence of work (weighted percentage of individuals that allocate positive labor hours)</i>				
Agricultural activities	0.61	0.67	0.57	0.59
Non-agricultural activities	0.12	0.23	0.07	0.07
Any rural activity (temporary/paid/unpaid)	0.68	0.88	0.62	0.64
<i>Intensity of work (weighted mean weekly hours allocated, conditional on working)</i>				
hours spent on agricultural activities	23.96 (16.69)	24.92 (16.60)	24.54 (16.72)	22.54 (16.66)
hours spent on non-agricultural activities	22.4 (16.7)	23.01 (15.62)	22.68 (18.71)	20.30 (17.44)
hours spent on any rural activity	28.68 (21.23)	34.02 (23.56)	26.92 (18.59)	25.10 (20.08)

*Note: - The data source is LSMS-ISA (2011/12, 2013/14, 2015/16).
- The sample considers only adult members (15-65 years) of rural households.
- Standard deviations are reported in brackets.*

As indicated in Table 2.1, more than one-third of adults in the sample reported zero hours of work, may be because they were unable to work in the reference week or they may choose not to participate a given activity at the current level of economic incentives.

Evidently, 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. Working in the non-agricultural sector is still rare. Only 12 percent report to have spent positive hours in non-agricultural activities. Conditional on working, an individual in rural Ethiopia allocates in a week on average, 24 hours for agricultural activities and 22 hours for non-agricultural activities.

The weighted percentage of individuals reporting positive weekly hours of work has decreased significantly from the 88 percent in 2010/11 to 62 percent in 2013/14. Also, conditional on working, the weighted mean weekly hours of work fell by more than seven hours between first and second rounds of the survey.

Further summary statistics is computed for the sub-groups of males and females from the sample in order check whether there are gender differences in labor allocation in rural Ethiopia. The statistics are reported below in Table 2.2.

Table 2.2: Labor allocation across rural activities in Ethiopia
(Summary statistics on pooled sample disaggregated by gender)

	Gender	
	<i>Male</i> (N=5,034)	<i>Female</i> (N=5,316)
<i>Incidence of work (weighted percentage of individuals that report positive hours of work)</i>		
Agricultural activities	0.72	0.51
Non-agricultural activities	0.11	0.14
Any rural activity	0.78	0.59
<i>Intensity of work (weighted mean weekly hours allocated, conditional on working)</i>		
hours spent on agricultural activities	26.32 (16.56)	20.61 (16.27)
hours spent on non-agricultural activities	19.49 (15.18)	25.06 (17.63)
hours spent on any rural activity	31.03 (20.79)	25.51 (21.39)

Note: - The data source is LSMS-ISA (2011/12, 2013/14, 2015/16).
 - The sample considers only adult members (15-65 years) of rural households.
 - Standard deviations are reported in brackets.

Time use patterns vary by gender: agricultural activities are more commonly carried out by male than female household members: approximately 72 percent of male engage in agricultural activities as compared to 51 percent of female. 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 percent) as compared to men (11 percent) reported to have allocated some positive labor hours to non-agricultural activities in the reference week. Besides, the reported weekly average hours spent on non-agricultural activities are 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 non-agricultural activities as compared to women.

In addition to agricultural and non-agricultural activities, it is important to consider household activities when analyzing labor allocation in rural areas where usually access to basic infrastructure is limited and traditional gender roles are deeply rooted. However, analysis in this paper does not cover such activities due to data paucity. The ERSS data does not provide sufficient information on household activities. Yet, it is well established that women in rural Ethiopia are predominantly engaged in time-consuming household activities such as collecting fuel wood or fetching water to the household on daily basis. The housework burden on women limits their time available to other works. Hence, once such household works are considered, total workload on women is expected to exceed by far that on men.

Table 2.3: Labor allocation across rural activities in Ethiopia
(Summary statistics on pooled sample disaggregated by age cohort)

	<i>Age cohort</i>			
	<i>15-25</i> <i>years</i> <i>(N=2,145)</i>	<i>25-35</i> <i>years</i> <i>(N=2,997)</i>	<i>35-45</i> <i>years</i> <i>(N=2,651)</i>	<i>45-65</i> <i>years</i> <i>(N=2,515)</i>
Incidence of work (weighted percentage of individuals that report positive hours of work)				
Agricultural activities	0.54	0.64	0.63	0.62
Non-agricultural activities	0.11	0.14	0.14	0.10
Any rural activity	0.62	0.71	0.70	0.67
Intensity of work (weighted mean weekly hours allocated, conditional on working)				
hours spent on agricultural activities	22.35 (15.9)	25.16 (17.31)	23.67 (16.68)	24.08 (16.45)
hours spent on non-agr activities	23.88 (17.38)	22.50 (16.31)	23.04 (17.68)	19.92 (14.90)
hours spent on any rural activity	26.59 (20.94)	30.08 (20.95)	29.27 (22.12)	28.07 (20.79)

Note: - The data source is LSMS-ISA (2011/12, 2013/14, 2015/16).

- The sample considers only adult members (15-65 years) of rural households.

- Standard deviations are reported in brackets.

Data disaggregating by age cohort shows that middle-aged adults (25-45 years) are the most involved age cohort in agricultural and non-agricultural activities, both in terms of participation and level of participation (hours of work). This age encompasses the years during life-course when earning and caring roles are most onerous. In contrast, young adults in the age group 15-25 years are the least involved in either agriculture or non-agricultural activities. This is probably because most individuals in this group are still attending school.

The main explanatory variables to be considered for this study are chosen to capture main factors that influence the relative shadow prices or marginal values of investing labor in various activities. We focus on individual and household attributes which undoubtedly play an important and direct role in determining the way people allocate their time. The variables include indicators of gender, age and education status; household composition (such as presence of children in the household); and households' wealth indicators (such as land and livestock holding). Furthermore, we also control region and year effects.

The major variable of interest for our analysis is *gender*, indicated by a dummy variable which takes a value of one for female adult members of a household, and zero otherwise. Females constitute approximately 51 percent of the adults in the restricted balanced sample used for the analysis in this paper.

In rural areas, gender plays an important role in labor allocation, especially in the non-agricultural sector. This is because it determines socio-economic characteristics of individuals by influencing their roles and asset ownership, which in turn influences labor market participation decisions. In most developing countries, women have less access to and control over resources and thereby they experience gender-based vulnerabilities, including extensive time burdens and limited legal benefits and protections. On the other hand, men have better access to resources that enable them to engage in such activities; hence they are more likely to diversify into non-agricultural activities. Previous studies have found significant gender bias in labor time allocation in Ethiopia, where women are found to be less likely to participate in off-farm activities given their greater time commitments within the household (Lemi, 2010).

The variables for *age*³ and *education level* are included to capture the effect of experience, which is believed to affect an individual's potential productivity, earnings, or reservation wage, as well as other individual characteristics affecting consumptive preferences. Education increases the range of work-related skills and the ability to acquire new skills. It makes individuals more employable and may increase the marginal value of time and opportunity costs of leisure. Educated individuals are likely to prefer to work outside agriculture (Salmon and Tanguye, 2015). There is evidence on the effect of education on non-farm employment participation in rural Africa, especially in more remunerative salaried and skilled employment (Barrett *et al.*, 2001; Lanjouw and Shariff, 2004). More than half of the adults in the restricted sample are illiterate (cannot read and write). Average years of schooling for the literate group is only about 4.75 (see Table A_1 in the Appendix).

Household composition is expected to determine in part an individual's allocation of time. Thus, we control *household demographics* by including variables for the number of infants and children in the household. The presence of children is presumed to promote labor market participation of adults for two reasons. First, the presence of children may indicate the need for additional income to support them, and thereby may lead to more participation of adults in the labor market. Within households with infants, women are more heavily burdened because they must take care of the children. Second, elder children assist in many household chores and thereby release adults from part of the housework and allow them to participate more in the labor market (Salmon and Tanguye, 2015). As children grow up, they start taking part in many types of household activities, allowing men to be less involved in such activities.

In order to control for the *household wealth and asset ownership*, which is likely to determine labor allocation decisions, we include land and livestock ownership among control variables. Previous studies from developing countries have shown that such assets are incentive and capacity variables (Ellis, 1998; Reardon, 1997). As a capacity, such

³ We also control for age square in order to capture the non-linear life cycle effect of experience.

wealth helps to facilitate investment in lucrative non-agricultural activities. On the other hand, more wealth may be translated to lower participation in non-farm activities due to higher level of income generated from other activities such as farming and the resulting increase in reservation wages.

Given the importance and increasing flows of remittances and other transfers in the context of Ethiopia, it is important to control for *non-labor income*⁴ of rural households. Less than one-tenth of the adults in the restricted sample belong to households that report to have received public transfers, remittances, and other unearned income. The impact of such non-labor income on labor force participation is a priori unclear. On one hand, non-labor income can raise reservation wages and discourage labor force participation of members of the household. On the other hand, non-labor income can relax credit constraint of a household and allow investment and participation in non-agricultural income generating activities. Many studies find the depressing effect of non-labor income on labor supply decisions to be much stronger in case of noncompetitive rural labor markets with high unemployment rate (Azizi, 2018).

Labor allocation is influenced by incidence of *shocks*. Thus, we included a dummy for whether a household faced *covariate shocks* such as drought, flood, landslides, heavy rain, or market fluctuations, which are expected to reduce the overall labor market participation by minimizing economic capacity of a community (Reardon, 1997; Lanjouw and Lanjouw, 2001). About 20 percent of adults in the restricted sample belong to households that reported to have faced such covariate shocks in the 12 months prior to the survey.

Furthermore, we included gender interaction terms 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. *Education status*, *number of infants* and *non-labor income* are interacted with gender.

⁴ It is important to account for the effect of household income which is expected to impact marginal productivity in different rural activities. We only consider the unearned non-labor income of the household since household labor income may give rise to endogeneity problems.

The presence of children may differently affect the way men and women allocate their time. Clearly, presence of young children increases incidence and average duration of housework, which is mainly carried out by women. Traditionally, women are responsible to take care of infants, thus having infants is likely to have relatively more effect on labor supply decisions of female than male. Taking care of children is a time-consuming activity that limits the time available to engage in agricultural and non-agricultural activities. Yet, a few studies claim that raising children and non-agricultural work are not necessarily competing activities in rural areas of developing countries, where there is extended family that support in taking care of children (Salmon and Tanguye, 2015).

Also, non-labor income is presumed to have differential effects on the labor supply decisions of male and female members of farm households. Empirical evidence suggests that the pressure on males, who are traditionally the breadwinners of the household, to participate in the labor market is reduced if the household gets non-labor income from different sources such as remittance (Matshe and Young 2004).

2.6. Discussion of results

This paper conducts extensive analysis on non-agricultural labor market participation and amount of time allocated using two-part model (TPM) regression technique⁵. The estimation approach accounts for the complex sample design of the ERSS data using provided survey weights in the calculation of robust standard errors for calculated regression coefficients.

It is important to check whether the model fits the data by exploring key assumptions of the model specification. We first test distribution of the dependent variable by plotting a histogram for non-agricultural work participants (see Figure A1 in the Appendix). As expected, the distribution is skewed to the right. This has direct implications on normality of error terms. TPM assumes that unobserved errors are normally distributed in the positive part of the distribution. The maximum likelihood estimator may be inconsistent when

⁵ Parameter estimates have been obtained using the Stata user-written command *twopm*.

normality assumption fails. Beyond graphical examination of the data, 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 a very small p -value. This is confirmed with the kernel density plot of residuals, which supports non-normality in residuals (see Figure A4 in the Appendix). One way to relax the normality assumption is to use non-normal distributions, such as the log-normal or the gamma distribution. Alternatively, one can use another less efficient estimation method to avoid biased maximum likelihood estimator.

The first part of the TPM is analyzed with a Probit model⁶ while 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 non-agricultural work) and the linear index of covariates, assuming the random component of the outcome follows gamma distribution⁷. 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 non-agricultural work are reported in Table 2.4.

2.6.1. 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 non-agricultural work) symmetric, we transform the dependent variable and check the histogram. 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 in Appendix).

⁶ The results are not sensitive to the model used in the first part. Running a Logit model gives identical results.

⁷ 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 positive skewness.

We opt here for a log-link, which is often the case with the gamma distribution since log-linear model transformation is preferred over linear in our estimations.

Table 2.4: GLM specification test: link and distribution

Link:	Log
Family:	Gamma
<i>Test for link function</i>	
Pregibon link test	-0.0705 (0.055)
<i>Modified Park test: $\chi^2(p\text{-value})$</i>	
ν coefficient	1.5091
$\nu = 0$: Gaussian	59.15 (0.0000)
$\nu = 1$: Poisson	6.73 (0.0095)
$\nu = 2$: Gamma	6.26 (0.0124)
$\nu = 3$: Inverse Gaussian	57.72 (0.0000)

Source: Author's own computation

We first perform goodness of link test (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 2.4). 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 of the dependent variable 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 distribution proves to be the most appropriate distributional family to model positive hours of non-agricultural work.

2.6.2. Results from Two-Parts Model (TPM)

Table A_2 in the Appendix presents the full results from the *two-part model (TPM)* estimation *with log-link and gamma distribution* 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 non-agricultural activity); while the second part presents coefficient estimates of the GLM version of TPM (for the analysis at the intensive margin: weekly hours allocated to non-agricultural work by participants). Then, marginal effects based on the combined results are presented in Table A_3 and discussed herein below.

Table 2.5: Results from tow-parts model (TPM) with log-link and gamma distribution
(Analysis of labor allocation to non-agricultural activities, at the extensive and intensive margins)

	Total sample	Male	Female
Gender (=1 if female)	1.093*** (0.35)		
Age	0.269*** (0.07)	0.224*** (0.08)	0.243** (0.09)
Age squared	-0.004*** (0.00)	-0.003*** (0.00)	-0.003** (0.00)
Education (=1 if literate)	1.179*** (0.18)	1.293*** (0.22)	0.857** (0.34)
Infants (No of Children < 6 years)	0.188 (0.22)	0.284 (0.21)	-0.105 (0.31)
Teenagers (No of Children 6-15 years)	-0.048 (0.14)	-0.173 (0.16)	0.150 (0.14)
Landholding (relative to marginal i.e. < 0.5 ha)			
Smallholder (0.5-2.0 ha)	-0.725*** (0.27)	-0.714** (0.29)	-0.747* (0.38)
Large (>2.0 ha)	-0.747 (1.11)	-1.345 (0.94)	-0.092 (1.40)
Livestock_holding	-0.215** (0.10)	-0.084 (0.12)	-0.353*** (0.11)
ln_Nonlabor_income	0.127* (0.07)	0.021 (0.05)	0.237** (0.10)
Covariate_shock	-0.260 (0.28)	-0.155 (0.40)	-0.265 (0.37)
Observations	10,350	5,034	5,316

Notes:

- The data source is LSMS-ISA (2011/12, 2013/14, 2015/16) considering only adult members (15-65 years) of rural households.
- The reported results refer to marginal effects based on the combined results from the first and second part of TPM (We have controlled for year and region effects).
- Robust standard errors are reported in parentheses.
- *, **, *** indicate significance at 10%, 5% and 1%, respectively.

The TPM with log-link and gamma distribution model fits the data better and is found to be more suitable for the analysis of hours of non-agricultural work⁸. The predicted hours of non-agricultural work from this model (2.36 hours) corresponds to the actual average hours of non-agricultural work in the sample (2.52 hours) (see Table A_1 in Appendix).

The main variable of interest in our analysis is the gender indicator variable. It is a dummy variable which takes a value of one for female adult members of a household, and zero otherwise. According to the results, females are more likely than males to participate in non-agricultural activities (as shown by the statistically significant coefficient in the first part of TPM model) and conditional on participation, females work longer hours in non-agricultural activities than their male counterparts (as shown by the statistically significant coefficient in the second part of TPM model) (see Table A_2 in Appendix). Although females are found to allocate more hours to non-farm work as compared to males at all ages, the difference is much greater for elderly than younger adults (see Figure A5 in Appendix). This may be due to the assumed log-link transformation.

The statistically significant positive marginal effects for the gender dummy implies that adult females involve in non-agricultural activities more than males on average by about 1.093 hours (see Table 2.5). Nevertheless, this 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 (see Table 2.6). This suggests that adult female from households with infants are less likely to engage in non-agricultural work as compared with their male counterparts, probably because taking care of infants is mainly in the female's domain of work and it is time-consuming.

⁸As a robustness check, we run alternative regression models (OLS, Tobit and TPM with square root-link and gamma distribution). The results are reported in Table A_4 in the Appendix. All the models yield highly similar results. The covariates have the same signs in all the models, although the OLS results are downward biased and inconsistent.

Most of the control variables have the expected signs. The marginal effects for the variable of age have statistically significant positive sign while age squared has a negative sign.

The positive sign of age infers that an increase in age is translated to higher expected hours of non-agricultural work until a certain age (37 years). This is due to greater likelihood of participation, rather than due to how much actual participants have worked (see Table A_2 in Appendix). Older cohorts are found to be more likely to engage in non-farm activities, reflecting the fact that non-agricultural activities are less physically demanding, and many of those who are less than 25 years old are still attending school.

The negative sign for age squared implies that the expected hours of non-agricultural work decreases with age after the age of 37 years (see Figure A6 in the Appendix). This is probably because a person would gradually start losing job opportunities after reaching a certain age or maybe it is because of 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, 2013).

This result is consistent with the findings of Abdullai and Crole-Rees (2001) in their study of households in Mali. According to their findings, the likelihood of participation in non-farm 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.

The results from our analysis also confirm the expected positive effect of education as educated individuals are likely to prefer to work outside agriculture (Salmon and Tanguye, 2015). Literacy increases the likelihood of participation in non-agricultural work, as well as the hours of non-agricultural work conditional on participation for both males and females. As can be seen from the gender disaggregated analysis, the magnitude of the effect of education is higher for males (1.29 hours) than females (0.86 hours). This result is confirmed by the negative coefficient for the interaction term of gender and education (see Table 2.6).

An increase in land size is found to be associated with a reduction in hours of non-agricultural work for smallholder farm households (with land sizes of between 0.5 and 2 hectares) relative to land-poor households (with marginal land sizes of less than 0.5 hectare); though no significant impact of land size is observed on the likelihood of choosing non-farm employment over farming (see Table A_2 in Appendix). With respect to livestock holdings, the result is significant only for female members of farm households. That is, herd size negatively influences women's participation in non-farm work but do not influence males' participation. This is not in line with the expected negative impact of livestock holdings on men who are mainly responsible for herding in rural areas. There is an economies of scale effect in grazing of livestock by males, but no such effects in female milking of livestock which may explain the differences in their hour's response.

The result from TPM also shows that an increase in non-labor income of a household is translated to higher expected hours of non-agricultural work; but this is due to higher likelihood of participation, rather than how much actual participants worked. This result is observed only for female members of farm households. A one percent increase in household's non-labor income is associated with a rise of 0.237 hour in the predicted weekly hours of non-agricultural work for adult female members of rural households. This result is further confirmed by a statistically significant positive coefficient of the interaction term of gender and non-labor income (see Table 2.6).

2.6.3. Addressing simultaneity bias in rural labor allocation decisions

Hours spent in each rural activity may 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* is included as an explanatory variable for the *hours of non-agricultural work* decision in order to account for potential interrelatedness and substitutions of work decisions. However, this may result in a simultaneity bias since *hours of agricultural work* may relate to unobservables biasing the results. Thus, the Control Function Approach (CFA) is employed to correct for such bias (Wooldridge, 2012).

CFA entails estimation in two stages. The first stage is estimation of the reduced form, where we analyze determinants of *hours of agricultural work*. Then, in the second stage, we analyze determinants of *hours of non-agricultural work* after including *hours of agricultural work* and the *residual from reduced form agricultural work model* as additional covariates in the structural model.

Note that, CFA model requires an exclusion restriction. That is, some strictly exogenous covariates need to be excluded from the structural model of *hours of non-agricultural work* to be used as instrumental variables with other covariates in the reduced form of potentially endogenous variable (*hours of agricultural work*). We use weather indicator (a measure of temperature) and access to extension program as instruments. These variables are exogenous, and they affect agricultural activities but not directly affect non-agricultural activities; and unobservable ability is presumably independent of such variables.

Table 2.6 illustrates different models, where agricultural work is not controlled for in Model 1, while it is controlled for in Model 2 and 3. Model 2 includes hours of agricultural work as extra covariate assuming it is exogenous while Model 3 accounts for the potential endogeneity of hours of agricultural work and the resulting simultaneity bias through CFA model estimation.

In the CFA, the significance of the coefficient of the residual in the structural model both tests and controls for endogeneity of *hours of agricultural work*. In our analysis, the predicted residual from the reduced form equation of the potentially endogenous variable (hours of agricultural work) is found to be statistically 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 the unobservables.

Table 2.6: Results from two-part model, controlling for effect of hours of agricultural work

	MODEL 1	MODEL 2	MODEL 3
Gender (=1 if female)	1.994*** (0.34)	1.679*** (0.35)	0.272 (1.09)
Age	0.244*** (0.07)	0.263*** (0.07)	0.365*** (0.09)
Age squared	-0.003*** (0.00)	-0.004*** (0.00)	-0.005*** (0.00)
Education (=1 if literate)	1.605*** (0.24)	1.511*** (0.25)	0.960** (0.38)
Infants (No of Children < 6 years)	0.612*** (0.21)	0.566** (0.22)	0.570** (0.23)
Teenagers (No of Children 6-15 years)	-0.023 (0.13)	-0.059 (0.14)	-0.145 (0.17)
Landholding (relative to marginal i.e. < 0.5ha)			
Smallholder (0.5-2.0 ha)	-0.727*** (0.27)	-0.652** (0.28)	-0.572* (0.29)
Large (>2.0 ha)	-0.709 (1.13)	-0.601 (1.15)	-0.581 (1.13)
Livestock_holding	-0.206* (0.10)	-0.201* (0.10)	-0.102 (0.10)
ln_Nonlabor_income	0.007 (0.05)	0.011 (0.06)	0.013 (0.06)
Covariate_shock	-0.254 (0.29)	-0.215 (0.31)	-0.410 (0.37)
Interaction terms			
Female*Education	-0.943*** (0.34)	-0.823** (0.34)	-0.635* (0.35)
Female*Infants	-0.973*** (0.21)	-0.925*** (0.20)	-0.888*** (0.21)
Female*Nonlabor_income	0.203** (0.08)	0.194** (0.08)	0.198** (0.08)
Control for hours of agricultural work			
Agr_hours		-0.027*** (0.01)	-0.026*** (0.01)
Predicted residual			-0.185** (0.09)
Observations	10,350	10,350	10,350

Notes:

- The data source is LSMS-ISA (2011/12, 2013/14, 2015/16) considering only adult members (15-65 years) of rural households.
- The reported results refer to marginal effects based on the combined results from the first and second part of TPM (We have controlled for year and region effects).
- Robust standard errors are reported in parentheses.
- *, **, *** indicate significance at 10%, 5% and 1%, respectively.

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 0.026 (less than two minutes) lower expected hours of non-agricultural work. The number of hours devoted to non-agricultural activities seems to be constrained by the number of hours allocated to agricultural activities marginally.

Nevertheless, there are some caveats which should be borne in mind when considering the results discussed above. First, wage is not included in the model because of paucity of data. This is because most of the non-agricultural works in rural areas are informal and non-monetary payments for labor is common. And 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, we considered exogenous variables that may affect individual's shadow price of time and the reservation wage rate.

Second, the analysis in this paper does not cover time allocated to household chores due to data paucity. The ERSS data does not provide sufficient information on household activities. In reality, rural women spend the long hours working at home and this is most likely to limit their time available to other works including non-farm works.

Third, the specification in this paper includes the attributes of only the decision maker and household characteristics. However, there are theories that suggest individuals' labor decision depends on his/her own attributes and those of other household members. This is difficult to control for in case of rural Ethiopia where there are variety of household types (monogamous households with the head and spouse, households with children and several adults, households with absentee head or spouse, and so on). It is complicated to jointly model labor supply decisions of members within a household and test for interdependence.

Finally, since the analysis is done on 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, economic, household and farm characteristics on non-agricultural participation.

2.7. Conclusion

This study examines the labor allocation decisions of adult members of rural farm households in Ethiopia using a pooled cross-sectional data from Ethiopian Rural Socio-economic Survey (ERSS). The analysis is done using Two-Parts Model (TPM), which provides a more realistic model of the labor market by distinguishing between non-agricultural work participation and intensity of participation (hours of non-agricultural work).

The descriptive analysis shows that agriculture remains to be the primary source of employment in rural Ethiopia. The result displays gender disparity in the allocation of labor time between agriculture and non-agricultural activities in rural Ethiopia. Agricultural activities are more commonly carried out by men: male members of farm households participate more and spend longer hours in agricultural activities. On the other hand, female members of farm households participate more and spend longer hours in non-agricultural activities.

The econometrics analysis also confirms that gender is, indeed, one of the important individual attributes associated with labor allocation decisions in rural Ethiopia. Female adult members of farm households are more likely to participate in non-agricultural activities; and conditional on participation, they spend more hours than their male counterparts in non-agricultural activities. However, female members of households with infants are less likely to participate in non-farm works and allocate relatively shorter hours than male members, conditional on 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 based 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 non-agricultural activities as well as the hours of agricultural work for both male and female, 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 non-agricultural activities only for female members of rural farm households.

There is trade-off in time allocation decisions in rural Ethiopia: the number of hours devoted to non-agricultural activities seems to be marginally constrained by the number of hours allocated to agricultural activities. Accordingly, the Control Function Approach (CFA) is used to control for the potential simultaneity bias related with the interrelatedness of agricultural and non-agricultural work decisions. Even after properly controlling for such bias, the effects of the incentive (pull/push factors) and capacity factors still hold, although the magnitudes of the effects decline slightly.

Although agriculture remains by far the primary source of employment in rural Ethiopia, considerable policy attention should be given to non-farm activities as an important complementary income source and livelihood strategy of farm households in rural Ethiopia, particularly as farming alone may fail to guarantee a sufficient livelihood for most rural households.

Attention should be given to the non-farm sector given the fact that it mostly employs individuals that probably face disproportionate constraints (such as burden of household responsibilities, lack of adequate infrastructure, and so on), 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 productive and income generating non-farm 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 the various factors that affect the decisions of male and female members of farm households.

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APPENDICES

Annex-I: Descriptive statistics

Table A_1: Summary statistics on the restricted sample of adults (N=10,350)

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 non-agricultural 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					
<i>Individual characteristics</i>					
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
<i>Household composition and wealth indicators</i>					
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
<i>Household wealth indicators</i>					
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
Non-labor_income	Non-labor income (unearned income)	2888.6	6096.4	0	42000
<i>Shock occurrence</i>					
Covariate_shock	(=1 if household faced covariate shocks)	0.19	0.39	0	1
<i>Instruments</i>					
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

Notes:

- *The data source is LSMS-ISA (2011/12, 2013/14, 2015/16).*
- *Only adult members (15-65 years) of rural households are considered.*
- *Survey weights are used when calculating mean and standard deviation.*
- *Weighted mean hours is computed on the sub-group of working individuals, excluding zero hours reported. Similarly, the average years of schooling is computed for the literate group. And 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 non-agricultural work for participants (untransformed)

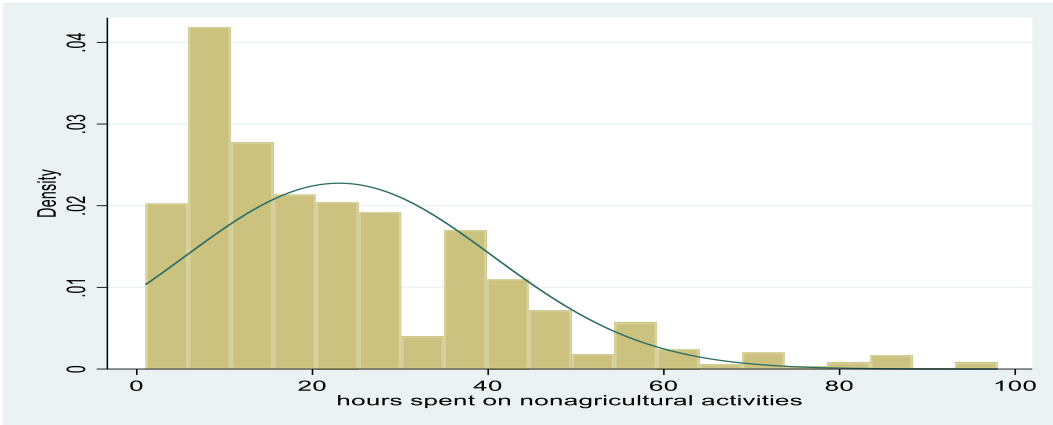


Figure A2. Histogram for logarithm hours of non-agricultural work (log transformation)

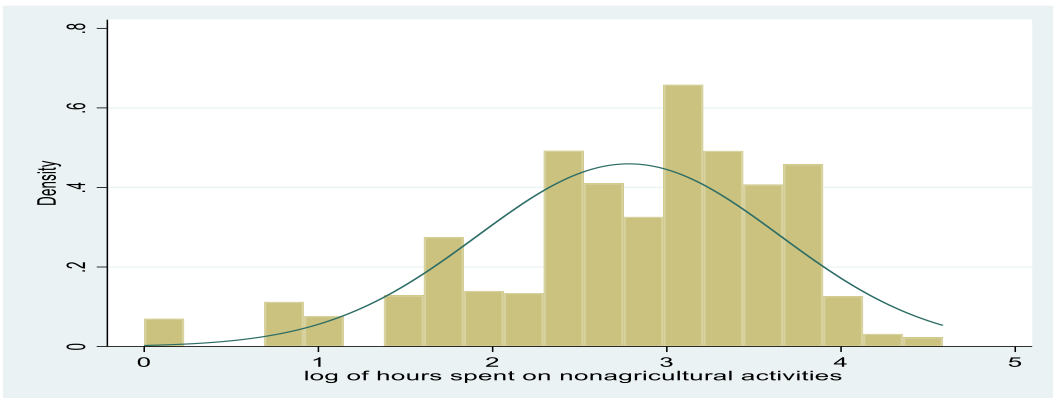


Figure A3. Histogram for square root of hours of non-agricultural work (square root transformation)

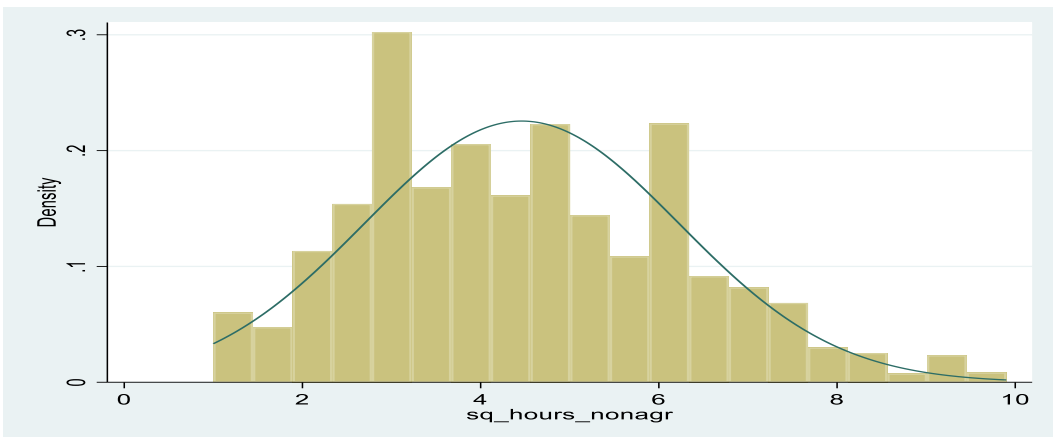


Figure A4. Kernel density plot of residual

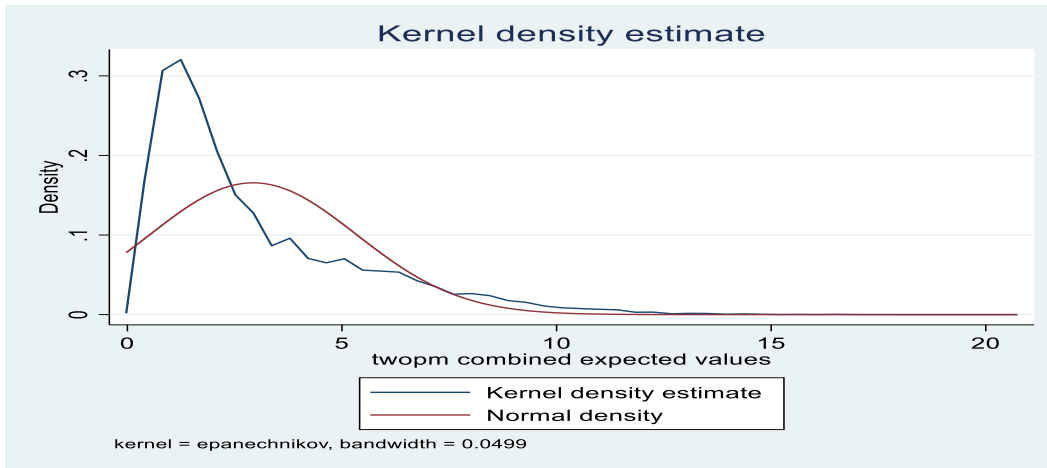


Figure A5. Gender differentials in hours of non-agricultural work

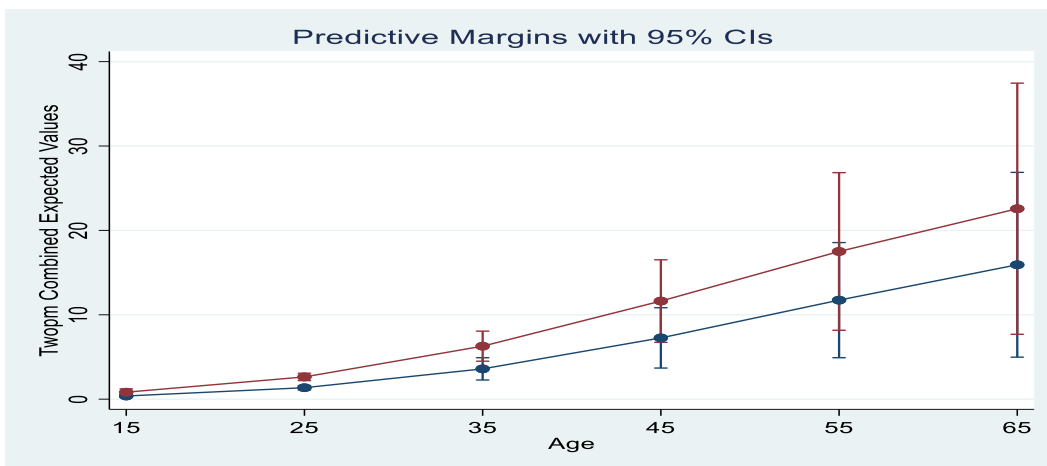
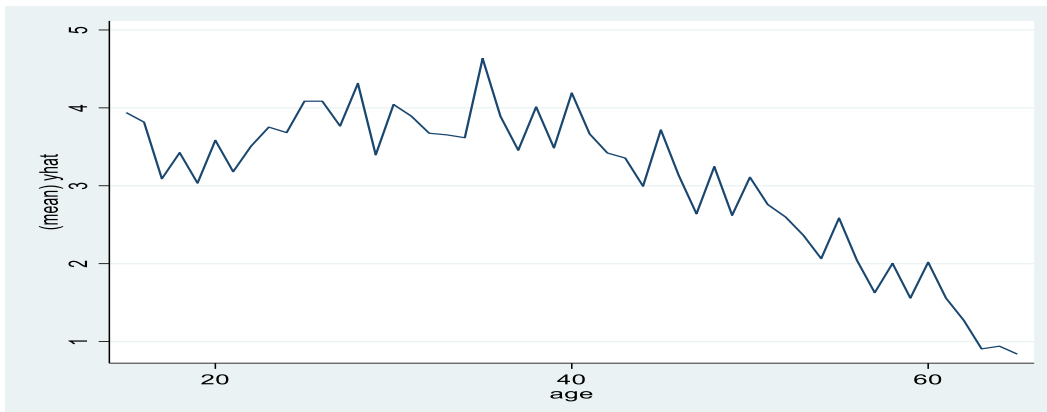


Figure A6. Age and predicted hours of non-agricultural work



Annex-II: Econometrics results

Table A_2: Results from two-part model with log-link and gamma distribution
(Coefficient estimates of the Probit and GLM versions of the model)

	MODEL 1	MODEL 2	MODEL 3
<i>Probit (decision to participate in non-agricultural work)</i>			
Female	0.270*** (0.06)	0.240*** (0.06)	-0.102 (0.23)
Age	0.070*** (0.02)	0.072*** (0.02)	0.091*** (0.02)
Age squared	-0.001*** (0.00)	-0.001*** (0.00)	-0.001*** (0.00)
Educ_status	0.314*** (0.05)	0.305*** (0.06)	0.211*** (0.08)
No of Child(<6yrs)	0.065 (0.06)	0.064 (0.06)	0.065 (0.06)
No of Child(6-15yrs)	-0.016 (0.04)	-0.018 (0.04)	-0.035 (0.04)
<i>Land holding (relative to marginal < 0.5 ha)</i>			
Smallholder (0.5-2 ha)	-0.077 (0.07)	-0.075 (0.07)	-0.061 (0.07)
Largeholder (> 2 ha)	-0.107 (0.32)	-0.100 (0.32)	-0.097 (0.32)
Livestock_holding	-0.050** (0.02)	-0.049** (0.02)	-0.031 (0.03)
ln_Non-labor_income	0.003 (0.02)	0.003 (0.02)	0.004 (0.02)
Covariate_shock	-0.108 (0.07)	-0.110 (0.07)	-0.148* (0.09)
<i>Region dummy and Year dummy (relative to 2011)</i>			
Tigray	0.047 (0.16)	0.048 (0.16)	0.031 (0.16)
Amhara	-0.242* (0.14)	-0.233* (0.14)	-0.135 (0.12)
Oromia	-0.180 (0.14)	-0.175 (0.13)	-0.133 (0.13)
SNNP	-0.293** (0.12)	-0.288** (0.12)	-0.263** (0.12)
yr_2013	-0.859*** (0.13)	-0.860*** (0.13)	-0.874*** (0.13)
yr_2015	-0.963*** (0.11)	-0.968*** (0.12)	-1.035*** (0.12)
<i>Gender interaction terms</i>			
Female*Educ_status	-0.174** (0.07)	-0.165** (0.08)	-0.134 (0.08)
Female*Child(<6yrs)	-0.172*** (0.05)	-0.170*** (0.05)	-0.165*** (0.05)
Female*Non-labor_income	0.035** (0.02)	0.035** (0.02)	0.036** (0.02)
Agr_hours		-0.003 (0.00)	-0.002 (0.00)
Predicted residual			-0.033* (0.02)
Constant	-1.799*** (0.31)	-1.779*** (0.32)	-1.428*** (0.30)

GLM (weekly hours of work spent on non-agricultural work)			
Female	0.383*** (0.09)	0.303*** (0.09)	0.046 (0.21)
Age	-0.010 (0.02)	-0.005 (0.02)	0.008 (0.02)
Age squared	0.000 (0.00)	0.000 (0.00)	-0.000 (0.00)
Educ_status	0.160* (0.09)	0.138 (0.08)	0.061 (0.08)
No of Child(<6yrs)	0.144** (0.07)	0.128* (0.06)	0.128** (0.06)
No of Child(6-15yrs)	0.015 (0.02)	0.004 (0.02)	-0.005 (0.02)
<i>Land holding (relative to marginal < 0.5 ha)</i>			
Smallholder (0.5-2 ha)	-0.173*** (0.06)	-0.146** (0.07)	-0.134* (0.07)
Largeholder (> 2 ha)	-0.119 (0.17)	-0.087 (0.16)	-0.085 (0.16)
Livestock_holding	-0.006 (0.01)	-0.006 (0.01)	0.007 (0.01)
ln_Non-labor_income	-0.002 (0.02)	-0.000 (0.02)	-0.001 (0.02)
Covariate_shock	0.063 (0.07)	0.082 (0.08)	0.062 (0.07)
<i>Region dummy</i>			
Tigray	-0.124 (0.24)	-0.091 (0.25)	-0.102 (0.25)
Amhara	-0.076 (0.15)	-0.037 (0.14)	0.037 (0.13)
Oromia	-0.159 (0.15)	-0.131 (0.14)	-0.104 (0.13)
SNNP	-0.156 (0.15)	-0.093 (0.15)	-0.077 (0.13)
<i>Year dummy (relative to 2011)</i>			
yr_2013	-0.095 (0.10)	-0.106 (0.10)	-0.116 (0.10)
yr_2015	-0.179** (0.07)	-0.181** (0.07)	-0.229*** (0.08)
<i>Gender interaction terms</i>			
Female*Educ_status	-0.110 (0.11)	-0.077 (0.11)	-0.049 (0.11)
Female*Child(<6yrs)	-0.126 (0.09)	-0.110 (0.09)	-0.104 (0.09)
Female*Non-labor_income	0.028 (0.02)	0.024 (0.02)	0.025 (0.02)
Agr_hours		-0.007*** (0.00)	-0.007*** (0.00)
Predicted residual			-0.024 (0.02)
Constant	3.210*** (0.35)	3.245*** (0.35)	3.509*** (0.43)
<hr/>			
Observations	10,350	10,350	10,350
<hr/>			

**Table A_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	MODEL 3
Female	1.994*** (0.34)	1.679*** (0.35)	-0.272 (1.09)
Age	0.244*** (0.07)	0.263*** (0.07)	0.365*** (0.09)
Age squared	-0.003*** (0.00)	-0.004*** (0.00)	-0.005*** (0.00)
Educ_status	1.605*** (0.24)	1.511*** (0.25)	0.960** (0.38)
No of Child(<6yrs)	0.612*** (0.21)	0.566** (0.22)	0.570** (0.23)
No of Child(6-15yrs)	-0.023 (0.13)	-0.059 (0.14)	-0.145 (0.17)
<i>Land holding (relative to marginal < 0.5 ha)</i>			
Smallholder (0.5-2 ha)	-0.727*** (0.27)	-0.652** (0.28)	-0.572* (0.29)
Largeholder (> 2 ha)	-0.709 (1.13)	-0.601 (1.15)	-0.581 (1.13)
Livestock_holding	-0.206* (0.10)	-0.201* (0.10)	-0.102 (0.10)
ln_Non-labor_income	0.007 (0.05)	0.011 (0.06)	0.013 (0.06)
Covariate_shock	-0.254 (0.29)	-0.215 (0.31)	-0.410 (0.37)
<i>Region dummy</i>			
Tigray	-0.131 (0.92)	-0.046 (0.92)	-0.138 (0.93)
Amhara	-1.117 (0.79)	-0.982 (0.76)	-0.423 (0.63)
Oromia	-1.089 (0.73)	-0.995 (0.70)	-0.768 (0.66)
SNNP	-1.515** (0.72)	-1.334* (0.68)	-1.197* (0.65)
<i>Year dummy (relative to 2011)</i>			
yr_2013	-3.527*** (0.59)	-3.553*** (0.60)	-3.624*** (0.60)
yr_2015	-4.135*** (0.44)	-4.150*** (0.45)	-4.522*** (0.48)
<i>Gender interaction terms</i>			
Female*Educ_status	-0.943*** (0.34)	-0.823** (0.34)	-0.635* (0.35)
Female*Child(<6yrs)	-0.973*** (0.21)	-0.925*** (0.20)	-0.888*** (0.21)
Female*Non-labor_income	0.203** (0.08)	0.194** (0.08)	0.198** (0.08)
Agr_hours		-0.027*** (0.01)	-0.026*** (0.01)
Predicted residual			-0.185** (0.09)
Observations	10,350	10,350	10,350

Table A_4: Comparing results from the alternative econometric regression models

	OLS	Tobit_pooled	Twopm_sqrt_link	Twopm_log_link
Female	2.061*** (0.36)	1.481*** (0.27)	1.932*** (0.33)	1.994*** (0.34)
Age	0.213*** (0.06)	0.296*** (0.07)	0.240*** (0.07)	0.244*** (0.07)
Age squared	-0.003*** (0.00)	-0.004*** (0.00)	-0.003*** (0.00)	-0.003*** (0.00)
Educ_status	1.439*** (0.19)	1.477*** (0.24)	1.563*** (0.22)	1.605*** (0.24)
No of Child(<6yrs)	0.614*** (0.17)	0.408* (0.22)	0.595*** (0.22)	0.612*** (0.21)
No of Child(6-15yrs)	-0.029 (0.12)	-0.054 (0.15)	-0.022 (0.14)	-0.023 (0.13)
<i>Land holding (relative to marginal < 0.5 ha)</i>				
Smallholder(0.5-2ha)	-0.682** (0.26)	-0.471 (0.29)	-0.718*** (0.26)	-0.727*** (0.27)
Largeholder(>2ha)	-0.899 (0.98)	-0.588 (1.31)	-0.647 (1.14)	-0.709 (1.13)
Livestock_holding	-0.308*** (0.11)	-0.220** (0.11)	-0.209** (0.10)	-0.206* (0.10)
ln_Non-labor_income	0.013 (0.05)	0.009 (0.07)	0.004 (0.05)	0.007 (0.05)
Covariate_shock	-0.213 (0.23)	-0.422 (0.29)	-0.237 (0.30)	-0.254 (0.29)
<i>Region dummy</i>				
Tigray	-0.307 (1.42)	-0.012 (0.76)	-0.115 (0.92)	-0.131 (0.92)
Amhara	-1.303 (1.10)	-1.107 (0.70)	-1.138 (0.80)	-1.117 (0.79)
Oromia	-1.444 (1.04)	-0.905 (0.66)	-1.109 (0.74)	-1.089 (0.73)
SNNP	-2.008* (1.05)	-1.385** (0.63)	-1.516** (0.73)	-1.515** (0.72)
<i>Year dummy (relative to 2011)</i>				
yr_2013	-4.622*** (0.83)	-3.809*** (0.61)	-3.527*** (0.60)	-3.527*** (0.59)
yr_2015	-5.100*** (0.72)	-4.348*** (0.49)	-4.086*** (0.43)	-4.135*** (0.44)
<i>Gender interaction terms</i>				
Female*Educ_status	-0.709* (0.42)	-0.830** (0.33)	-0.899** (0.34)	-0.943*** (0.34)
Female*Child(<6yrs)	-1.040*** (0.17)	-0.879*** (0.20)	-0.970*** (0.22)	-0.973*** (0.21)
Female*Nonlab_income	0.263* (0.13)	0.181** (0.07)	0.215** (0.09)	0.203** (0.08)
Constant	2.631* (1.38)			
Observations	10,350	10,350	10,350	10,350

CHAPTER THREE

HETEROGENEOUS IMPACTS OF SHOCKS ON CHILD TIME ALLOCATION: EVIDENCE FROM RURAL ETHIOPIA

Abstract

Poor rural households in developing countries are exposed to a plethora of shocks that usually have unpleasant consequences. One repercussion is the use of child labor as an alternative coping strategy in the presence of shocks. This is, especially true when households face a binding adult labor constraint and in settings of imperfect labor, insurance, and credit markets. We empirically test this using a panel data from rural Ethiopia and employing multilevel mixed effects tobit models. According to the results, idiosyncratic shocks (such as illness or death of family member) tend to drive children to work more outside home in both agricultural and non-agricultural activities while covariate shocks (such as flood, drought, heavy rain, and landslides) increase total hours of child work including household activities such as fetching water and firewood collection. Heterogeneity analysis indicates the existence of gender bias in child labor when households face shocks – only girls experience harmful effects from shocks, in terms of increased hours of work. The results of the study also support the hypothesis that non-labor income and access to credit ease the effect of shocks on child labor. Furthermore, there is clear causal evidence on the adverse effect of excessive hours of child work on children's educational attainment (measured by age-adjusted schooling outcome (GAGE)). Hence, there is a need for properly designed public policies and interventions that enable finance-constrained households to withstand shocks without resorting to child labor.

Keywords: Shocks, Idiosyncratic, Covariate, Child labor, Rural Ethiopia

JEL Codes: J01, J13, J22

3.1. Introduction

Rural households in low-income countries are highly exposed to several shocks which can be classified into *idiosyncratic shocks* (that are specific to a household such as illness or death of family member, asset loss and crop damage) and *covariate shocks* (such as flood, drought, heavy rain, and landslides that affect all households in the same village though the extent of the effect may differ among households).

Along with greater exposure to such shocks, rural households in many developing countries have limited resilience capacities and are less equipped to deal with risks; having fewer assets, scarce opportunities to diversify income, limited access to credit and insurance, and low or inadequate social protection provisions. They commonly rely on informal mechanisms such as use of child labor, own savings, remittances from family members or relatives residing elsewhere or receive help within their social networks⁹ (Bandera et al., 2014; Beegle et al., 2006; Beegle et al., 2008). In particular, empirical evidence from developing countries shows higher tendencies to use child labor as a buffer against unexpected shocks, especially when households face a binding adult labor constraint (Bhalotra and Heady, 2003; Debebe, 2010).

Child labor is a topic that has been receiving growing attention among the trends and issues related to rural employment. This is because child labor remains to be one of the development challenges that most developing countries face despite various policies being implemented to combat it. Worldwide, 218 million children aged from 5 to 17 are involved in child labor and most of them reside in low-income countries (ILO, 2017). Child labor is particularly prevalent in the least developed countries, where slightly more than one in four children are engaged in harmful activities that may compromise their physical, mental, social, or educational development (UNICEF, 2019).

⁹ In this regard, an example of informal social networks from rural Ethiopia is the labor sharing arrangement known as “Debo” that renders labor upon need and relax labor endowment constraint (Admassie, 2001; Debebe, 2010).

Ethiopia is one of the countries with the highest rates of child labor in the world, with well over 40 percent of children aged 5–17 years are engaged in child labor (CSA and ILO, 2018; CSA, UNICEF Ethiopia and C4ED; 2020).

The main aim of this paper is to test the hypothesis that exposure to shocks increases households' reliance on child labor in the context of rural Ethiopia. To be precise, this paper endeavors to examine the extent to which idiosyncratic and covariate shocks lead to greater intensity of child work in different rural activities.

The analysis in this paper is based on the presumption that child labor is bad in parental preferences and that parents will not opt for it unless they face a compelling situation. It is also based on the commonly based hypothesis that access to credit, insurance, social networks, and other means that relax financial and labor constraints play a role of insuring shocks and lessen the pressure to draw on child labor when households face shocks (Dillon, 2013; Dumas, 2015). In this regard, the current paper probes whether availability of coping strategies, such as non-labor income and credit access, help households ease the pressure to rely on child labor when families are hit by shocks. Furthermore, the study aims to assess the effect of long working hours on educational attainment of school-aged children in rural Ethiopia.

According to existing literature, the main reason for prevalence of child labor is poverty in conjunction with other aggravating circumstances such as vulnerability to adverse shocks that may significantly affect household income (Bandara et al., 2015; Dillon, 2013; Beegle et al., 2006; Duryea et al., 2007). Other reasons include family situations (such as orphan hood, a parent's inability to work, or a large number of siblings), barriers to education (like distance from school, inability to cover school fees and related costs), and cultural considerations surrounding children (some cultures encourage children to work to develop skills, others consider children as assets to generate income in time of poverty and supporting elderly).

Whatever the cause, there is wide consensus that child labor is undesirable as it has adverse effects on child well-being, household welfare and on the overall country's development potential. Children in child labor encounter a variety of perils that may lead to long-term physical and psychological effects. One unpleasant repercussion of child labor is its long-term effect on human capital formation. It is widely perceived to impede the educational attainment of children both directly (dropping out of school) and indirectly (less time for schoolwork may lead to grade repetition). Participation of children in work activities for long hours and often at the cost of school attendance is very common in rural areas. Such work participation could prevent children from acquiring education, cast shadow on academic performance; and deny them a wide range of benefits associated with education.

Child labor robs girls and boys of their childhood, heightens their risk of falling behind and compromises their future earning potential and career development, making them even more vulnerable to poverty and exclusion. Furthermore, the practice of child labor affects household welfare by trapping poor households in the cycle of poverty and it has intergenerational persistence (Beegle et al., 2009; Beegle et al., 2008; Haile and Haile, 2012; Woldehanna et al., 2005).

Despite the prevalence of child labor in rural areas of most developing countries and the resulting repercussions, studies on this subject are meager especially when it comes to the influence of various shocks against working hours and school attendance of children.

The existing few studies on the area have several limitations. First, most of the previous studies use aggregate shock measures and lump different types of work activities together into one, making it difficult to address how different types of shocks may impact different forms of child labor in various ways. Besides, they overlook domestic chores, which take prominent share of child labor in most African countries including Ethiopia. Second, the existing empirical literature on child labor in developing countries focus almost exclusively on the extensive margin using dichotomous measures for whether the child participates in certain economic activities or not, with no explanation of the substantial variation in hours allocation across different activities. Third, the link between shocks, child labor and other coping mechanisms (such as non-labor income and credit access) remains largely

unexplored. Fourth, most of the previous studies are based on cross-sectional data; thus, more likely to suffer from confounding effects due to inability to separate the effects.

This paper contributes to the literature in several different ways. First and foremost, it contributes to better understanding of the effect of shocks on child time allocation in the context of a rural subsistence economy. The analysis in this paper focuses on rural Ethiopia, where the majority population dwells, mainly depending on traditional agriculture as their main source of livelihood. Second, this paper provides a comprehensive view of how households allocate child labor when faced with different types of shock induced stress. This is done by distinguishing between idiosyncratic and covariate shocks and examining effects of the different shocks on intensity of child work as measured by hours of work in different activities including domestic chores.

Third, the paper provides a thorough investigation to grasp direction and magnitude of effects of shocks on child labor in the presence of other coping mechanisms. In this regard, this research complements current efforts in the literature, which focus on implications of credit rationing and lack of insurance mechanisms on the impact of shocks on child vulnerability in developing countries.

Fourth, this paper recognizes the fact that child labor does not always work through the commonly assumed channel of deterring school enrolment and shifts the focus of the child labor discourse from its interaction with school enrolment, to that with educational attainment to improve understanding of the adverse impact and inefficiency of child labor.

Fifth, the analysis in this paper is based on an appropriate empirical methodology that accounts for a number of empirical issues, including endogeneity, the multilevel and mixed process features of the child outcomes, as well as the fact that the child outcome measures (hours of work and the measure of educational attainment) are left-censored. The available panel data is exploited using an appropriate empirical strategy that allows us to control for unobserved time-invariant characteristics, which can potentially influence the household's child labor decision.

Last but not least, findings from this study help to identify potentially important determinants of child labor and as a result, point at mechanisms that can be used to tackle it. And a better understanding of the nature and trade-off between child labor and schooling in rural Ethiopia is essential to formulate policies aimed at curbing child labor and its repercussions.

The rest of the paper is organized as follows. Section two provides a brief literature review on child labor from developing countries. Section three describes the data used for the analyses and provides summary statistics of key variables. Section four specifies the model to be used for the empirical analysis. Section five discusses methodological challenges with potential solutions. Section six presents the estimation results and discusses the main findings of the study. The last section summarizes the main findings and concludes.

3.2. Review of relevant literature

From a theoretical point of view, shocks may increase or decrease child labor depending on the type of shock that households experience and the opportunities for children to work. When households in low-income countries face shocks, such as crop loss or the death of a family member, that adversely affect their income and labor endowment, they tend to rely on child labor to smooth consumption (argument I: child work is used as a buffer against shocks). An alternative narrative is that shocks that affect the marginal product of labor in certain activities decrease child labor by reducing the efficiency of children's work and opportunity costs of time (argument II).

Most of the empirical studies from developing countries in Africa focus on the first argument and tests to what extent children are used as a buffer against shocks. For instance, Beegle et al. (2003) and Beegle et al. (2006) have provided robust evidence of a causal positive relationship between transitory shocks (such as crop loss) and intensity of child labor in Tanzania. Households respond to such shocks by increasing their use of child labor at the cost of lower school enrollment.

Only a few studies consider the importance of distinguishing between different categories of shocks and work activities (market and domestic work) in the analysis of child labor. Bandara et al. (2014) considered two types of shocks in Tanzania: income shocks (agricultural shocks) and non-income shocks (the death of parents or relatives) and find a significant effect of only agricultural shocks in terms of increased hours of child work especially for boys and adverse effects on school attendance, mainly for girls. Similar results are reported by Beegle et al. (2008); where crop shocks lead to increases in hours of agricultural work for boys and hours of household chores for girls in Tanzania.

Dillon (2013) analyzes the impact of crop loss and morbidity at the intensive and extensive margin of children's market and domestic work in northern Mali. Dillon's findings suggest that whether child labor is used as a risk coping strategy highly depends on the type of shock and the type of work: health shocks significantly affect child labor at the intensive margin, but it has no effect on their school attendance. On the other hand, crop loss increases children's work participation on farm work at the expense of school attendance; but access to credit (measured by access to a bank account) mitigates the impact through decreases in the number of hours worked by girls.

In addition to examining the effect of shocks, few studies have extended their analysis to look into the heterogeneity in vulnerability depending on availability of alternative coping mechanisms such as asset ownership, credit access and informal networks. Most studies show that the extent to which child labor is used as a buffer is lower when households have asset holdings and access to credit. For instance, Beegle et al. (2006) find that economic shocks induce child labor but less so when household owns assets.

The issue of child labor happens to be of a great relevance in Ethiopia given the high prevalence of child labor; yet relevant studies in the country are limited. Much of the prior work from Ethiopia focused on the non-economic factors associated with child labor and schooling (Admassie, 2001; Haile and Haile, 2007). Only recently, few studies have tried to relate shocks with child labor. For instance, Debebe (2010) estimated the differential impact of shocks on child labor and confirmed the claim that child labor (farm and domestic child labor) is used as a household's self-insurance mechanism. The author further

examined the effect of an informal social network in rural Ethiopia on child labor hours both at normal times and at times of shocks. The results highlighted the substantial benefits of membership in a labor sharing arrangement that renders labor upon need, in terms of lessening the pressure to draw on child labor at times of idiosyncratic shocks, but not covariate shocks. Also, Colmer (2013) assesses the effect of climate variability on child labor and schooling outcome. His results imply that climate variability increases the number of hours worked on farm which decreases the number of hours worked at home, suggesting substitution between the two activities.

More recently, Dinku et al. (2018) examined the effect of parental health shocks on the allocation of children's time using the Young Lives Survey panel data for Ethiopia. According to the results, paternal illness increases children's time spent income-generating work while maternal illness increases time spent in domestic work. The results suggest that child time allocation is influenced by traditional gender roles where maternal illness has a relatively large effect on girls while paternal illness has a relatively large effect on boys.

In addition to the resulting work burden on children, there are also studies that endeavor to look into the impact of shocks on schooling on children in Ethiopia. Woldehanna and Hagos (2012) show that both idiosyncratic shocks and covariate shocks have a statistically significant effect on the risk of children dropping out of primary school. Similarly, Woldehanna and Gebremedhin (2015) show that shocks (as instrument for child work) have negative effects on child achievement in education.

3.3. Data description and summary statistics

The analysis in this paper is based on a rich and nationally representative data from the Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) of the World Bank in collaboration with the Central Statistical Agency (CSA) of Ethiopia. We use data from the three rounds (2010/11, 2012/13 and 2014/15). The dataset is appropriate for the proposed analysis of shock-specific adjustments in child labor as well as the effect of child labor in schooling outcomes. In particular, the panel structure allows to control for unobservable effects and to exploit the dynamics in child work and schooling status over time.

The dataset entails information about shocks faced by households in the past 12 months prior to the survey and their employed coping strategies. Also, there is detailed information on individuals and household characteristics, including information on time use of all household members aged seven and older. This includes information on hours spent in the previous week of the survey working on agricultural activities, non-agricultural activities, temporary/casual work or salaried job, and unpaid apprentice. There is also data on hours and minutes spent yesterday fetching water and collecting firewood. In our analysis, the former information is used to proxy for child time spent in economic activities while the latter is used to proxy for household activities. In fact, household activities include many other time-taking domestic activities (such as cooking and serving meals, cleaning, caring for younger siblings, infirm, disabled, or elderly household members), which are not considered in the time-use data employed for this study. Since we do not have data on all kinds of domestic chores, we only use information on hours spent fetching water and firewood to proxy for housework.

Given our research objectives, we restrict our sample to rural households with children aged 7-17 years in line with the child labor literature from developing countries. The lower age range is consistent with the official starting age of school in Ethiopia. The education system consists of an eight-year primary education cycle, thus, a child that is enrolled on time is expected to complete primary schooling by the age of 15. Our sample includes adolescents and extend the upper age to 17 years considering the possibilities of delayed enrollment or repeating grades in rural Ethiopia. Consequently, the restricted sample consists of 1,727 children observed in three waves, resulting in a pooled sample of 5,181 children aged 7-17 years. Approximately 53 percent of observations in our data set are boys and 47 percent are girls.

The descriptive statistics of the variables used for the analysis are reported in Annex-I. Table A.2 in Annex-I reports the summary statistics for the pooled sample of children aged 7-17 years. Then the sample is separated into sub-samples of children in households that had experienced a shock and those that had not. The respective descriptive statistics for the sub-samples are reported in Table A.3 in Annex-I.

Overall, 2,927 children in our sample (about 56 percent) report to have allocated some time to economic activities in the reference week while 2,291 children (about 44 percent) report to have spent some time each day fetching water and collecting firewood. Most children engage in agricultural activities (about 54 percent) while only about five percent of the children report positive hours of non-agricultural work. Paid employment for children is rare; only few children are engaged in wage employment or non-farm family businesses; but many households rely on children to work in the house or on family farms.

In terms of age, young children between the ages of 7 and 10 years are more likely to be in child labor. This could be due to the delay in school enrollment in most rural areas. More than half of the children in this group had never attended school and were illiterate. These children worked noticeably more than those who had attended school. While the average time spent on economic activities among the latter group is 22 hours per week, it is 26 hours among those in the former group.

There is apparent gender inequality in terms of incidence and intensity of child work. About 66 percent of the boys and 46 percent of girls reported to have spent some time in economic activities in the past seven days. And conditional on working, boys spend on average about five more weekly hours in economic activities relative to girls (see Table 3.1).

Table 3.1: Average hours of child work (conditional on working), disaggregated by gender and age

	Weekly hours spent on economic activities (agricultural and non-agricultural)			Daily hours and minutes spent on household activities (fetching water and collecting firewood)		
	All	Boys	Girls	All	Boys	Girls
All Children	23.31 (17.02)	25.16 (17.74)	20.43 (15.41)	1.41 (1.20)	1.41 (1.22)	1.41 (1.19)
Children aged 7-10 years	23.5 (17.50)	25.81 (18.54)	20.56 (15.64)	1.41 (1.25)	1.53 (1.44)	1.34 (1.13)
Children aged 11-14 years	23.38 (16.94)	25.16 (17.47)	20.54 (15.67)	1.38 (1.18)	1.35 (1.12)	1.41 (1.21)
Children aged 15-17 years	22.68 (16.24)	24.06 (17.09)	19.64 (13.74)	1.49 (1.19)	1.39 (1.10)	1.55 (1.25)

Note: Figures in parenthesis are standard deviations.

Source: Own computation based on the restricted sample of children (7-17 years old) from rural Ethiopia.

Figure 3.1a clearly shows that boys are more likely than girls to engage in economic activities for excessive hours: 13 percent of the boys (relative to only 6 percent of the girls) report to have spent more than 42 hours a week in economic activities (see Figure 3.1a). On the other hand, girls are assumed to shoulder a greater responsibility for housework in most societies. 57 percent of the girls (and only 32 percent of the boys) in the sample had spent some time fetching water and collecting firewood in the previous day. The majority of the girls in our sample are involved in domestic chores for less than two hours per day (see Figure 3.1b).

Figure 3.1: Hours of child work (intensity), disaggregated by gender

Figure 3.1a: Percentage of children engaged in economic activities grouped by weekly hour bracket and sex

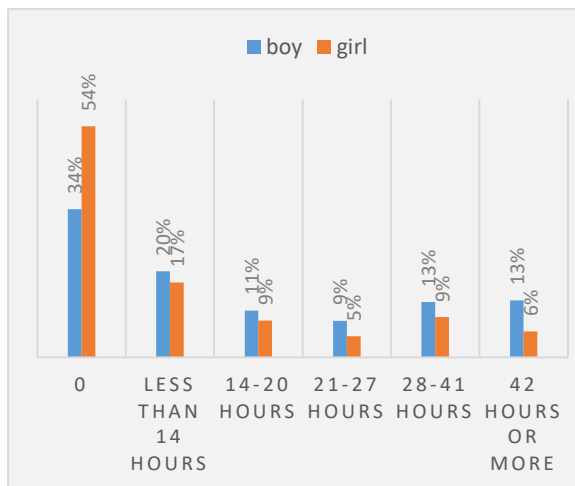
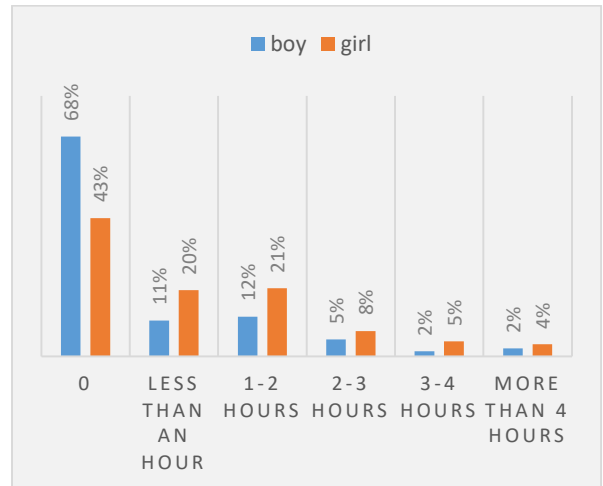


Figure 3.1b: Percentage of children performing household chores grouped by daily hour bracket and sex



Overall, boys are more likely than girls to engage in economic activities at every age cohort and weekly hour range. On the other hand, girls are much more likely than boys to perform household chores at every age cohort and daily hour range.

Figures 3.2a and 3.2b below demonstrate that gender gap in both economic- and household-work participation increases with age.

Figure 3.2: Incidence of child work, disaggregated by gender

Figure 3. 2a: Percentage of children that report positive hour spent in economic activities per week, by age cohort and sex

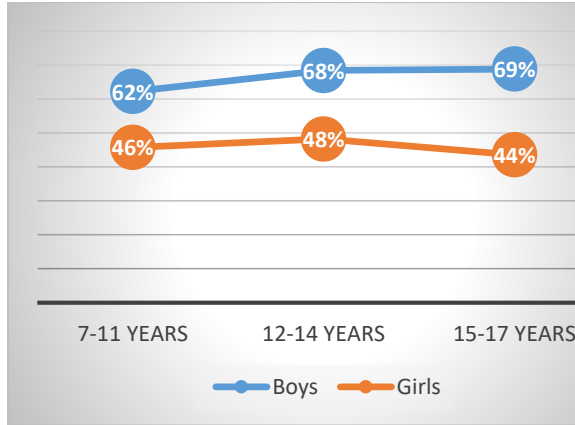
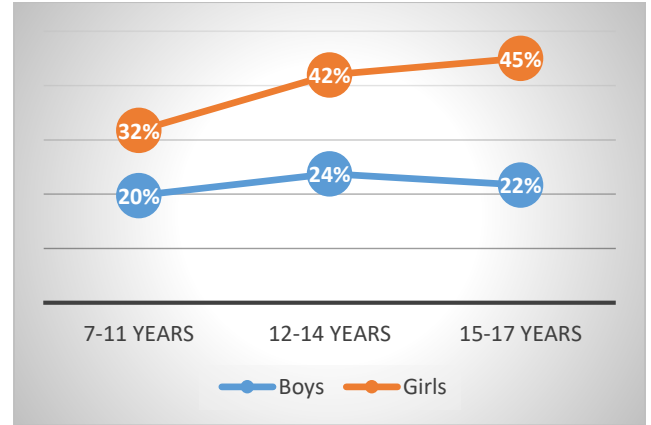


Figure 3.2b: Percentage of children performing household chores for at least one hour per day, by age cohort and sex

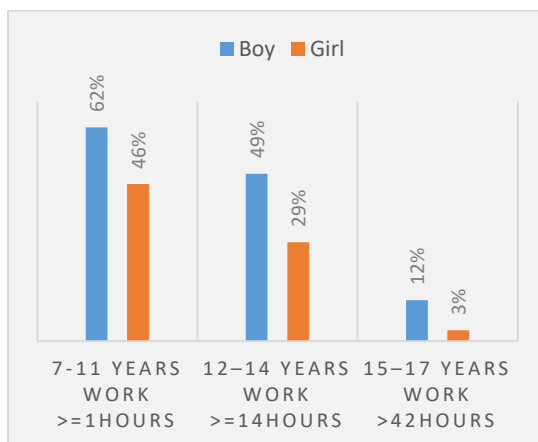


Child labor

There are different criteria for identifying any given work as child labor. According to International Labor Organization’s (ILO) definition, child labor refers to a child under 12 who participated in an economic activity for at least one hour per week, a child aged 12 to 14 who participated for at least 14 hours per week (two hours per day), and a child aged 15 to 17 who participated for at least 43 hours per week (ILO, 2017).

Figure 3.3: Prevalence of child labor in rural Ethiopia

a) Based on ILO’s criteria for identifying any given work as child labor



b) Based on UNICEF’s criteria for identifying any given work as child labor

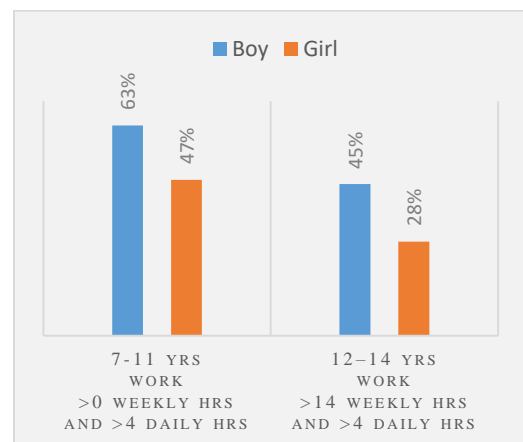


Figure 3.3a depicts the prevalence of child labor in rural Ethiopia based on ILO's standard. According to the statistics computed based on the above definition (with the concept of child labor restricted to economic activities), More than half of children under 12 years and about one third of children aged between 12 and 14 years are in child labor.

As clearly shown in Figure 3.3a, boys appear to face a greater risk of child labor than girls; boys account for more than 60 per cent of all children in child labor. And the gender gap increases with age. The gender difference in child labor incidence is 16 percentage points for 7–11 year-olds, and it rises to 20 percentage points for 12–14 year-olds. But this may be in part a reflection of an under-reporting of girls' works relative to that of boys. Girls may be more present in less visible and therefore under-reported forms of child labor such as household chores in their own homes. In rural Ethiopia, girls' work in agriculture is often invisible, and on top of that their contribution to domestic work is not given any economic values.

An alternative definition of child labor that takes into account household chores is the one suggested by United Nations Children's Fund (UNICEF). For children aged 5-11 years, child labor is defined as domestic chores in excess of 28 hours per week (that is four hours per day) or any income-generating work; for children aged 12-14 years, child labor is defined as domestic chores in excess of 28 hours per week or income-generating work is excess of 14 hours per week (ILO, 2017). Figure 3.3b depicts the prevalence of child labor in rural Ethiopia based on UNICEF's criteria for identifying any given work as child labor. The statistics computed based on this definition yields similar results on the prevalence of child labor. The statistical finding also supports the claim that the prevalence of child labor is somewhat higher for boys than for girls, even after controlling household chores.

Shocks and hours of child work

Households in rural Ethiopia are exposed to several shocks which affect their welfare. About one-fourth of the children reside in rural households that reported to have been affected by a shock in the previous 12 months. Specifically, 20 percent of the children reside in households that were hit by covariate shocks (such as drought, flooding, heavy

rain, landslides and market related shocks) and nine percent of the children reside in households hit by idiosyncratic shocks (such as illness and death of household members, loss of crops or livestock) (see Table A.3 in Annex-I).

Rural households use different mechanisms to cope with the aforementioned shocks. Most commonly, they rely on informal mechanisms such as use of own savings, sell assets, and use finance from different sources (borrowing and transfers), reallocate labor (they use child labor as a buffer against shocks when faced with binding adult labor constraints).

In order to check if there is significant difference in child time allocation between households that experienced a shock and those that did not, the sample is separated into two sub-samples based on occurrence of shock. Mean hours of child work, schooling as well as most other covariates are similarly distributed in two sub-samples (see Table A.3 in Annex-I).

Conditional on working, average hours of child work is slightly higher when a child belongs to a household that has experienced a shock compared to children from households that did not report any shock in the last 12 months (see Table 3.2 below). Relative to households not hit by shocks, children residing in households hit by a shock spend on average 1.65 more weekly hours on economic activities and 0.4 hours (24 minutes) daily hours fetching water and firewood.

Table 3.2: Shocks and average hours of child work, conditional on working

	<i>Full sample</i>	<i>Sub sample of children in households that had experienced a shock</i>	<i>Sub sample of children in households that had not experienced a shock</i>
	<i>Mean (Std.Dev.)</i>	<i>Mean (Std.Dev.)</i>	<i>Mean (Std.Dev.)</i>
<i>Weekly hours spent on economic activities</i>	23.46 (17.5020)	24.54 (18.9083)	22.89 (16.3089)
<i>Daily hours and minutes spent on household activities</i>	1.41 (1.2042)	1.71 (1.443)	1.31 (1.0946)

Source: Own computation based on the restricted sample of children (7-17 years old) from rural Ethiopia.

3.4. Empirical model specification and explanation of variables

3.4.1. Model specification

In this section, we outline the model specifications used to identify the determinants of child time allocation decisions within households. First, we specify an appropriate model to be used to address the first objective of this paper (that is, to test whether shocks lead to an increase in child labor and examine the extent to which access to credit and non-labor income help to mitigate the effect of shocks). Then, another appropriate model is specified to address the second objective of this paper (that is, to assess the impact of child labor on their educational attainment).

Modelling the impact of shocks on child work

The direct effect of shocks can be examined based on the following specification:

$$child_work_{ijt} = \beta_0 + \beta_1 x_{ijt} + \beta_2 h_{jt} + \varepsilon_{ijt} \quad (3.1a)$$

Where $child_work_{ijt}$ is the outcome of interest (weekly hours spent in economic activities and daily hours spent in household activities) for child- i in household- j and wave- t of the survey round; x_{ijt} contains a set of controls for child characteristics while h_{jt} contains a set of controls for household characteristics including the main variable of interest (*shocks*) that do not vary across children (i). And ε_{ijt} is a random error term. We have also controlled for time and region effects but not indicated in the model specification for the sake of simplicity.

Rural activities are likely to be affected differently by different types of shocks. In order to be able to discern among the heterogeneous effects of different categories of shocks, we use separate indicators for *idiosyncratic shocks* (such as illness and death of any household member) and *covariate shocks* (such as drought, flood, landslides, and heavy rain) as indicated by $idio_shock_{jt}$ and cov_shock_{jt} respectively in model specification (3.1b).

$$child_work_{ijt} = \beta_0 + \beta_1 x_{ijt} + \beta_2 h_{jt} + \beta_3 idio_shock_{jt} + \beta_4 cov_shock_{jt} + \varepsilon_{ijt} \quad (3.1b)$$

Shocks are often postulated to influence child time allocation decisions at household level. We expect the coefficient of shocks to be positive ($\beta_3, \beta_4 > 0$) as certain shocks may force households to use more child labor. Many studies have shown that absence of well-functioning insurance and credit markets in rural areas forces households to use child labor and other adverse coping mechanisms (such as sell of productive assets and adjustment in food intake) (Beegle et al., 2003; Beegle et al., 2006; Bandara et al., 2014; Hazarika and Sarangi, 2008).

In this paper, we test the importance of access to credit and insurance markets in determining the reaction of households to adverse shocks and household decisions concerning children's activities. Specifically, we test whether access to credit and non-labor income (as self-insurance mechanism) help families to ease the effect of shocks on child labor. This is done by interacting shock indicators with the variables for the buffering mechanism that we intend to ideally examine (*household non-labor income* and *access to credit*). In particular, we estimate the following model specification:

$$child_work_{ijt} = \beta_0 + \beta_1 x_{ijt} + \beta_2 h_{jt} + \beta_3 idio_shock_{jt} + \beta_4 cov_shock_{jt} + \beta_5 buffers_{jt} + \beta_6 idio_shock_{jt} * buffers_{jt} + \beta_7 cov_shock_{jt} * buffers_{jt} + \varepsilon_{ijt} \quad (3.1c)$$

Coefficients of the interaction terms capture the differential impacts of shocks among children from households with different status, in terms of different levels of non-labor income and access to credit. We expect negative values for coefficients of the interaction terms ($\beta_6, \beta_7 < 0$) since non-labor income and access to credit are expected to reduce the resulting shock induced child labor. But, it is important to note that benefits of such coping mechanisms may be limited in case of certain types of shocks, say covariate shocks that affect a whole community. There are some studies which have looked into the ambiguous effects of different buffering mechanisms depending on the type of shocks faced (Beegle et al., 2003; Beegle et al., 2006; Debebe, 2009; Dillion, 2013; Dinku, 2018).

Modelling the impact of child work on children's educational attainment

It is well documented that child time allocation decision is based on a trade-off between child labor (additional income today at the cost of future income) and schooling (higher earnings potential in the future) (Beegle et al. 2006). In order to control for such a trade-off, hours of child work are included in the regression equation for educational attainment (see specification (3.2)).

$$child_education_{ijt} = \alpha_0 + \alpha_1 x_{ijt} + \alpha_2 h_{jt} + \alpha_3 child_work_{ijt} + \mu_{ijt} \quad (3.2)$$

where $child_education_{ijt}$ is a measure of educational attainment for child- i in household- j and survey round- t ; and $child_work_{ijt}$ is hours of child work.

The coefficient of interest is α_3 and the hypothesis to be tested is whether child labor has a negative impact on educational attainment ($\alpha_3 < 0$).

x_{ijt} and h_{jt} contain sets of controls for child and household characteristics similar to specification (3.1a) and h_{jt} is constant across children within the same household. These set of variables facilitate identification of the impact of child labor by controlling for observable characteristics that may affect work and educational outcomes. Failure to control for such variables may cause omitted variable bias. And μ_{ijt} is a random error term.

3.4.2. Explanation of variables

The outcome variables to be considered in the current analysis of child time allocation decisions are ***hours of child work*** and ***educational attainment of children***.

In this study, the term '*child work*' refers to any form of participation by children in paid or unpaid work activities. Specifically, the dependent variables for the analysis of child work on the intensive margin are '*weekly hours spent on economic activities*' (agricultural and nonagricultural) and '*daily hours and minutes spent on household activities*' (fetching water and firewood).

Economic activities alone do not capture all the activities undertaken by working children. Thus, children's involvement in household activities is considered in addition to economic works in order to get a comprehensive understanding of child work in rural areas of many developing countries where children, especially girls, spend substantial amounts of time in household activities. This is a significant contribution to the existing literature on child labor since most of the previous studies focus exclusively on economic activities, mainly because of paucity of data on household activities and opacity in the distinction between economic and housework in rural settings. Such analysis results in understatement of child labor; particularly girls' participation in domestic chores and the impact on their educational attainment is understated (Mavrokonstantis, 2011).

Most research on the effect of child labor on educational attainment of children use imperfect measures of learning outcomes such as school enrolment, attendance, drop out and years of schooling (Beegle et al., 2008; Beegle et al., 2009; Ersado, 2005; Woldehanna and Hagos, 2012). Few studies used better indicators of educational attainment such as test scores (Mavrokonstantis, 2011; Watson, 2008; Woldehanna and Gebremedhin, 2015). But, test scores do not reflect educational attainment in the context of a developing country like Ethiopia where enrollment is still a major development challenge for policy makers.

In this paper, we use a measure that gives information on school outcomes, beyond the concept of attendance. Specifically, the following index for age-grade distortion is used for the analysis of educational attainment of children.¹⁰

$$Grade_for_age = 100 * \left[\frac{years\ of\ schooling\ of\ the\ child}{Age\ of\ the\ child - 7} \right] \quad (3.3)$$

The index captures age-appropriate grade achievement, where all dispersions in age are measured from the age of seven years old, which is the official age for starting primary school in Ethiopia.

¹⁰ This measure was initiated by Psacharopoulos and Yang (1991) in their study educational attainment in Venezuela, and followed by many other studies on child schooling (Haile and Haile, 2008; Gebremedhin et al, 2016).

It is appropriate measure of school outcomes for developing countries such as Ethiopia, where child labor is an issue and there are cases of combining school with work (Admassie, 2001; Haile and Haile, 2008; Gebremedhin et al, 2016). It is an attractive measure to use as it accounts for grade attained conditional on age. Children with the same completed grades of schooling are treated differently depending upon their age, except if the actual completed grade is zero.

The measure takes a value of 0 if a child has never attended school. For those children who have had some schooling, the index measures if a child is in the appropriate grade for his or her age. The index takes a value greater than 0 but lower than 100 if a child is over-age relative to the child's grade due to late entry or perhaps the child has repeated grades or had dropped out. An index value of 100 indicates complete schooling attainment, where the child is in the appropriate grade for his or her age. Some of the children in the sample have a value greater than 100, which may be because they started their education at an earlier age than the entry age.

Variables of main interest

The main variables of interest for the analysis of child work are the shock indicators. The estimation is based on constructing a covariate shock and idiosyncratic shock from these sets of shocks. ***Idiosyncratic shock*** is captured by using a dummy variable that takes the value of 1 if any member of the household faces serious illness or death during the past 12 months prior to the survey, else 0. ***Covariate shock*** is captured by a dummy variable that takes the value of 1 if a household reported to have faced drought, flood, heavy rain or landslides in the last 12 months prior to the survey, else 0.

Both shock indicators are relevant in the context of rural Ethiopia. Covariate shocks have a significant negative effect on agriculture production, which is the main economic activity in rural Ethiopia. Given that working children in rural Ethiopia are mainly engaged in agriculture, such shocks affect children's marginal product of labor on the family farm. Idiosyncratic shocks, such as death or illness of adult family members, are common shocks faced by poor households in many developing countries including Ethiopia. And it is well

documented that such shocks induce sudden changes in family composition, which places additional and heavy responsibilities on children in rural households (Debebe, 2010).

Control variables

In estimating the effects of shocks, it is necessary to control for other variables that may affect a family's child time allocation decisions. Thus, we include a broad range of controls, including observable individual and household characteristics relevant to children's work and school decisions. This is helpful to deal with omitted variable bias with respect to shocks and child labor. The covariates are chosen based on theoretical considerations, findings in the literature, and availability in the dataset. Only variables that were statistically significant in preliminary estimations are kept for the final multilevel model specification. This is mainly because of the computational burden of the multilevel technique and the need to estimate a parsimonious specification. All the covariates are explained in greater detail in Annex-I.

We control for ***child specific sociological factors*** such as a child's age, gender and the child's relationship to the household head. These factors are shown to affect allocation of child time to different activities (Admassie, 2001; Cockburn and Dostie, 2007; Ersado 2005; Woldehanna and Hagos 2012). In particular, it is vital to control for gender in order to identify potential gender disparities in work and schooling outcomes, which is widely observed in developing countries.

Controlling for exogenous variables such as ***demographic composition of the household*** is helpful to capture the intra-household dynamics as well as to deal with between-household differences (household heterogeneity) that may partly determine which households choose to send their children to work and for how long. Household demographic characteristics are also among the factors identified in the literature to affect the allocation of children's time with indeterminate impact a priori.

There may be a positive association between child labor and the ***number of infants in households*** as children, in particular girls, may be required to take care of their younger siblings (Haile and Haile, 2012). Also, ***the number and composition of adult household***

members affects the intensity of child labor depending on the relationship between adult and child. It may be the case that large labor endowment (which reflects households' earning potential) may be associated with fewer child work hours and greater opportunity for school attendance. The presence of adults, particularly adult women, in the household relieves girls of part of their housework burden and may reduce children's work time through substitution or economies of scale effects (Admassie, 2001).

The nature of headship is also another potential determinant of child labor, particularly in Ethiopia (Admassie, 2001; Cockburn and Dostie, 2007; Woldehanna et al., 2005). Very few households in our sample are headed by female who are in most cases not married. They are a relatively more vulnerable group as they have lower access to productive resources which affects their productive ability and the intra-household allocation of resources. As a result, children in female-headed households may have greater work burden to generate resources to sustain the family. Hence, a negative association between schooling and female heads of families might be expected.

Sex of household head may differently affect the involvement of boys and girls in economic and household work. It is hypothesized that children participate more (less) in market work and less (more) in housework if they have the same (opposite) sex as the household head. For instance, girls that reside in male-headed households may be expected to involve more in housework for excess hours, especially if the mother is not present in the household.

Several empirical studies confirm that age and education of the household head are among the demographic variables identified as having an impact on child labor (Beegle et al., 2006; Ersado, 2005). They capture the effect of experience which is believed to affect individual's productivity in different activities and earnings. Education level of the head is a good proxy for income of the household since it is pre-determined and unlikely to be endogenous with respect to child outcomes (Bandara et al., 2014). Parental education enhances human capital and therefore wealth without improving the employment prospects of children. Furthermore, parental education captures differences in preferences concerning a child and it has intergenerational implications.

Land and livestock holdings are critical complements of labor in the rural areas of developing countries and are plausibly correlated with child labor intensity. They are included in our analysis as important controls for household income and wealth since they are means of income generation and serve as collateral for borrowing. It is difficult to conclude a priori, whether household wealth has a positive or negative effect on child labor in a particular setting. Child labor is normally portrayed as being negatively associated with household wealth ('income effect'/luxury axiom), implying that poverty is the main reason for child labor. While for poor households, child labor may provide a way of supplementing the insufficient resources and income of the family; the better off rural households (with large land and livestock holdings) are able to forgo the income the child brings to the household (Cockburn and Dostie, 2007). On the contrary, a positive association can be rationalized (that is, the better off rural households use more child labor) in case of rural agricultural settings with imperfect markets ('substitution effect'/wealth paradox) (Bhalotra and Heady, 2003).

We also control for region of current residence and time fixed effects in order to capture macroeconomic and local conditions, including labor market conditions. The regional dummies control for all time-invariant unobservables at the region level that could be correlated with child labor and shocks, such as differences in culture and social norms with respect to child labor, influence of social institutions and practices that may affect household's attitude and allocation of resources to children, and the availability of governmental and non-governmental safety nets.

3.5. Methodological challenges and potential solutions

The literature on child time allocation raises a number of methodological issues. Perhaps the most obvious are the nature of data and how to measure child outcomes (child labor and educational attainment); which shape the estimation strategy. Other potential problems include attenuation bias, between and within household selection bias, and endogeneity of child labor and schooling decisions (Mavrokonstantis, 2011). Some of the problems are discussed herein below.

3.5.1. Dealing with the presence of large number of zeros in the data: Tobit models

An obvious challenge in analyzing time allocation decisions is the presence of large number of zero-value observations in the data, as it is common to see zero time spent in many activities. And the choice of estimation models depends on the nature of zeros (i.e. whether zeros are true zeros or not). Zeros can occur either because the individual never does the activity in question (a true zero) or because the individual does the activity but did not do the activity on the reference week.

There is a long tradition among time-use researchers of using *Tobit models* to estimate the effects of covariates on the long-run average amount of time spent in an activity, assuming that the zeros arise from censoring (Wooldridge, 2012). Yet, Tobit may yield biased and inconsistent results when the zeros arise not from censoring, but from a mismatch between the reference period of the data and the period of interest. That is, the zeros arise because time use data is collected over a short period of time and the reference period is not long enough to capture children's long-run work patterns. Some of the zeros would have been positive, had the data been gathered in another time period (Stewart, 2013). In such cases, *Ordinary Least Square (OLS)* is appropriate as it considers the potentially large amount of random day-to-day variation in the amount of time spent in many activities and recognizes the effect of random factors (such as the weather and own or other family members' illness) on long-run time use decisions.

In this paper, the analysis of hours of child work is based on a Tobit model assuming that observed zero values are due to censoring. The model accounts for the large number of children that are not engaged in any type of child work without having to restrict the sample to only working children; thereby it addresses the potential problem of sample selection bias (Wooldridge, 2012). Similarly, the impact of child labor on educational attainment is estimated using Tobit because the outcome variable (GAGE) has observed zero values for more than 35 percent of children in the sample.

The standard Tobit models for the analysis of hours of child work and educational attainment are given by equations (3.4a) and (3.4b) respectively.

$$child_work_{ijt} = \begin{cases} (child_work_{ijt})^* & \text{if } (child_work_{ijt})^* > 0 \\ 0 & \text{otherwise} \end{cases} \quad (3.4a)$$

$$child_education_{ijt} = \begin{cases} (child_education_{ijt})^* & \text{if } (child_education_{ijt})^* > 0 \\ 0 & \text{otherwise} \end{cases} \quad (3.4b)$$

Where the latent variables given by $(child_work_{ijt})^*$ and $(child_education_{ijt})^*$ denote the desired hours of child work and educational attainment respectively; while the observed dependent variables given by $child_work_{ijt}$ and $child_education_{ijt}$ denote the actual hours of child work and educational attainment.

The standard Tobit model assumes corner solutions where the latent and the observed dependent variables are equal when the latent variable is greater than zero, but the observed variable is zero when the latent variable is negative (Tobin, 1958).

3.5.2. Dealing with endogeneity of shocks: Multivariate analysis

An important challenge in estimating the effect of shocks on child work is the possible *endogeneity of shocks*. The assumption of exogeneity of some shocks (for example idiosyncratic shocks) can be questioned as the occurrence of such shocks may relate with unobservable household characteristics that may also partly explain child work, and therefore could bias the estimation results. Disentangling the impact of shocks on child labor is difficult because of the complex relationship between a family's living standards and child labor decisions. In practice, children living in specific conditions may be systematic and more likely to face shocks. For example, poor and less forward-looking households might be both more prone to shocks and, at the same time, more inclined to sending their children to work (because they place less value on formal education).

Prior studies try to address endogeneity problems using different identification strategies. Few have applied child/household level Fixed Effects (FE) regression techniques, controlling for the effect of a wide range of unobservable time-invariant child/household characteristics. They empirically investigate whether shocks are correlated with household, child, or parental characteristics taking into account unobserved time-invariant factors that might affect both shocks and children's outcomes. While this does not preclude the possibility of correlation with unobservable variables, it does increase the plausibility of the view that shocks are exogenous, and effectively random with respect to household labor practices (Bandara, et al., 2014).

In this paper, we address the aforementioned problems using *multivariate analysis*, as an alternative to panel data analysis. The multilevel model is considered to be more appropriate for two reasons. First, it helps to deal with the panel structure of the data (that is, children are observed overtime and a child's responses over time are correlated with each other) by considering observations across waves as one level in the hierarchical model. The multilevel model is special case of random effect models (Rabe-Hesketh and Skrondal, 2012) and it has advantage over the fixed effects model in panel analysis (which controls household level variables but is unable to estimate the effect of any variable that does not vary within clusters). Besides, multilevel models allow the option to control for complex survey designs in exploiting the panel structure of the data.

Second, the multilevel model is an appropriate model to deal with the hierarchical/clustered structure of our data. That is, children are nested within households and outcomes of children from the same household are correlated as they are affected by the same unobserved household characteristics, and they share common household-level random effects. Multilevel modelling allows to recognize the hierarchical structure of our data by allowing the error term in our regression be structured according to the known hierarchy¹¹. Besides, multilevel model is appropriate for our analysis since some explanatory variables

¹¹ Multilevel modelling generates the correct standard errors and efficiently weights the between and within variations to generate the estimated effect based on the residual variances within and between individuals.

are measured at household level and others at child level. The model provides within estimates of child level variables and allow inclusion of household level variables.

Specifically, we estimate a three-level hierarchical model with clustered standard errors. Level one refers to occasions (children observed at different waves) while levels two and three refer to child level and household level respectively. For the sake of simplicity, we consider only levels two and three and present the following parsimonious multilevel model for a given point in time:

$$y_{ij} = \beta_0 + \beta_1 x_{ij} + \beta_2 h_j + v_{ij} + u_j \quad (3.5)$$

where y_{ij} denotes the outcome variables (hours of child work and grade-for different ages) of child- i nested in household- j expressed as a function of a vector of child level covariates (x_{ij}) that vary between- and within-clusters and a vector of household level covariates including occurrence of shocks (h_j). Child and household level random error terms, given by v_{ij} and u_j respectively, are assumed to be independently and normally distributed with zero mean and constant variances given by σ_v^2 and σ_u^2 .

The assumption of independent households is violated in the presence of clustering, where groups of children may be in the same household. This is dealt with by allowing child-level intercept to vary across households in order to explicitly model dependence among children within the same household.

The causal interpretation of results from the analysis in this paper relies on the assumption of independence of the household-level error term, conditional on the regressors included in the model. The estimates from the random effects model specified in Eqn. (3.5) are consistent if the distributional assumption of the household-level error term holds: $u_j / x_{ij}, h_j \sim N(0, \sigma_u^2)$ and $E(u_j / x_{ij}, h_j) = 0$. However, the independence assumption can be violated due to the existence of unobserved household characteristics that are correlated with observed child characteristics that affect child work (that is, $cov(x_{ij}, u_j) \neq 0$). More specifically, the assumption will not hold if there are unobserved random variables that affect households' exposure to shock and children's outcomes at the same time.

Identification comes from time variations in household's exposure to shocks for the same child, and the underlying assumption of the model is that these variations are exogenous, conditional on the set of independent variables. In practice, children living in a household with specific socio-economic conditions may be systematically more likely to be exposed to shocks, but the time variation in shocks should not be related to children's outcomes (Bratti and Mendola, 2014). Failure to account for endogeneity problem resulting from such potential correlation results in biased estimation.

3.5.3. Dealing with endogeneity of child labor: Control Function Approach (CFA)

Investigating the effect of child labor on educational attainment entails endogeneity problem as the variable for child labor (hours of child work) is likely to be affected by other individual and household features and decisions on child work and schooling could be taken simultaneously. The presence of unobserved variables that might affect both decisions could bias estimation results, and it may be difficult to draw a causal relationship between child work and educational attainment. Certain child characteristics may make one child in the household more likely to work than another. Also, unobservable household characteristics may partly explain whether and for how long a child is sent to school. For instance, household preferences to send children to work or school could be related to the household head's attitude and desired educational level for his/her child. In this regard, it is not appropriate to consider work participation/amount of work time as an exogenous determinant of decisions regarding children's schooling.

Prior studies have used different identification strategies to deal with the aforementioned problem. For instance, few studies have used fixed effect models that help to isolate the true impact of child labor on the educational attainment of the children by removing household characteristics or socio-economic factors which may also impact their educational attainment (Woldehanna and Hagos, 2012). There are also studies that use Instrumental Variable (IV) method to deal with the endogenous nature of child labor. Other studies use bivariate models to capture potential trade-offs and joint responses of child labor and schooling outcomes to changes in other variables though they do not establish a causal relationship between such variables (Ersado, 2005; Dillon, 2013).

In this paper, the endogenous nature of child labor is dealt with by employing multivariate analysis and the Control Function Approach (CFA) in two steps (Wooldridge, 2012). CFA entails two stages. In the first stage, hours of child work ($child_work_{ijt}$) is regressed on the exogenous explanatory variables (x_{ijt}, h_{jt}) and the instruments (z) as follows:

$$child_work_{ijt} = \beta_0 + \beta_1 x_{ijt} + \beta_2 h_{jt} + \beta_2 z + \varepsilon_{ijt} \quad (3.6a)$$

In the second stage, a child's educational attainment ($child_education_{ijt}$) is regressed on the same set of exogenous explanatory variables (x_{ijt}, h_{jt}), but with hours of child work ($child_work_{ijt}$) and the predicted values of the residual from the first stage ($\hat{\varepsilon}_{ijt}$) included as additional covariates. It can be written as follows:

$$child_education_{ijt} = \alpha_0 + \alpha_1 x_{ijt} + \alpha_2 h_{jt} + \alpha_3 child_work_{ijt} + \alpha_3 \hat{\varepsilon}_{ijt} + \mu_{ijt} \quad (3.6b)$$

In the CFA, significance of the coefficient for the predicted residual proves the existence of the assumed endogeneity problem, which will be controlled by including the predicted residual (Wooldridge, 2012).

Note that, CFA requires exclusion restriction. That is, we need a valid instrument that explains a substantial proportion of variation in the endogenous variable (hours of child work). And the instrument must have effect on the outcome of interest through the endogenous variable and cannot be correlated with the residual. It is very difficult to find such a variable as most factors influencing the schooling decision will also influence the working decision.

In this paper, households' experiences of socio-economic shocks are used as instruments for child work. Shocks are found to be strongly correlated with the endogenous variable (child labor) once the other independent variables are controlled for; but not correlate with unobservables that also determine educational attainment. Unobservable ability is presumably independent of shock indicators that are excluded from the equation of educational attainment.

There is strong evidence of the validity of such instruments. Beegle et al. (2003) and Watson (2008) use the incidences of transitory shocks (such as drought, crop failure and pests and disease shocks) the household face as successful instrument to child work (that is, they are relevant and exogenous). They claim that these events are unexpected and when they happen households might need extra labor so as to sustain life and survive them. The incidence of shocks are expected to increase child labor but not to affect children's educational outcomes directly except through the channel of child labor. They argue that such shocks are significant sources of variation in child labor and are likely to only affect the outcome (educational attainment) through the endogenous variable (child labor) and not through other variables.

3.6. Discussion of estimation results

This section presents the main empirical findings, first from the investigation of the impact of shocks on child work, and then the effect of hours of work on educational attainment of children, considering only rural households in Ethiopia. For all the analysis, multilevel models are fitted, incorporating children nested within households. Each model has two random-effects components to account for unobserved heterogeneity among children: a random intercept at the household-level, and a random intercept at the child-level.

The log likelihood ratio (LR) test is significant in all the multilevel models, indicating substantial variability in the variance of the intercept (see Annex II). The reported likelihood-ratio tests show that there is enough variability between households to favor a mixed-effects Tobit over a standard Tobit regression. This is confirmed by looking at the intra-class correlation (ICC), which refers to the fraction of variance that can be attributed to each level. The fact that the ICC is greater than zero indicates the existence of clustering in our data. Furthermore, the ICC signifies that about 20 percent of the variance in child labor is at household level.

The mixed-effects Tobit regression model estimations report the estimated variance components and the fixed effects. But we are interested in the marginal effect of the covariates on the observed outcome. Thus, we estimate the average marginal effect of a

covariate on the expected value of the actual hours worked and the results are presented under Annex-II.¹²

3.6.1. Effect of shocks on child work

For the analysis of child labor, we are mainly interested in shocks as determinants of child work. Yet, we control for child and parent characteristics, household composition, household status indicators (land and livestock holding, non-labor income and access to credit) as well as region and year effects in order to reduce potential omitted variable bias of the coefficient of shock indicators.

Heterogeneity in the effect of shocks based on categories of shock and type of activity

We examine some avenues of heterogeneity in analyzing the effect of shocks. We begin by examining heterogeneity in the effect of shocks based on categories of shock and type of activity. Our investigations consider two types of shocks: idiosyncratic shocks (such as illness or death of family member) and covariate shocks (such as flood, drought, heavy rain, and landslides) are separately included in order to discern the potential heterogeneous effects of different categories of shocks. We also distinguish between economic and household activities to get a comprehensive view of how households allocate child time endowment. Furthermore, splitting up child labor in its components is helpful to scrutinize the heterogeneous impact of shocks as different categories of shocks may not equally affect hours of child work in different activities. It also helps to see if potential coping mechanisms work differently for different types of child work.

Table 3.3 below displays results for determinants of different types of child work with dependent variables defined as: hours spent on economic activities in the last seven days, and hours spent on household activities (fetching water and collecting firewood) yesterday by children (boys/girls aged 7-17 years).

¹²Mixed-effects Tobit method fits mixed-effects models (fixed effects and random effects) for continuous responses where the outcome variable is censored.

Table 3.3: Estimation results for child work (hours spent in economic and household activities)

	Weekly hours spent on economic activities	Daily hours and minutes spent on household activities
<i>Shock indicator dummies</i>		
(=1 if household faced Idiosyncratic shocks)	4.127** (1.90)	0.172 (0.11)
(=1 if household faced Covariate shocks)	0.965 (0.62)	0.105*** (0.04)
<i>Child characteristics</i>		
Sex dummy (=1 if boy)	6.581*** (0.49)	-0.499*** (0.03)
Age of child	0.589*** (0.11)	0.060*** (0.01)
Relation to household head (=1 if biological child)	-1.526 (1.15)	-0.146** (0.07)
<i>Parent characteristics and household composition</i>		
Sex dummy (=1 if male headed)	0.208 (1.06)	-0.024 (0.06)
Age of household head	-0.022 (0.03)	0.001 (0.00)
Years of schooling of household head	-0.187* (0.11)	0.002 (0.01)
No of infants(<6yrs)	0.136 (0.32)	0.013 (0.02)
No of male adults	-1.278*** (0.29)	-0.032* (0.02)
No of female adults	-0.564* (0.33)	-0.127*** (0.02)
<i>Household status indicators (coping mechanisms)</i>		
Landsize_percapita	1.265 (1.41)	-0.076 (0.09)
Livestock_holding	0.197* (0.10)	-0.015** (0.01)
Log(Non-labor_income)	-0.167 (0.12)	0.009 (0.01)
Dummy for credit access (=1 if household has access to credit)	1.515*** (0.52)	0.046 (0.03)
<i>Observations</i>		
	5,181	5,181
<i>Left-censored observations</i>	2,254	2,890
<i>Uncensored observations</i>	2,927	2,291

Notes:

- The data source is LSMS-ISA (2011/12, 2013/14 and 2015/16), with restricted sample of children (7-17 years).
- Average marginal effects (dy/dx) are reported with robust standard errors in parentheses.
- *, **, *** indicate significance at 10%, 5% and 1%, respectively.

The estimated results in Table 3.3 indicate that idiosyncratic shocks have a statistically significant effect on hours spent on economic activities while the covariate shocks have a statistically significant effect on time spent on household activities. In terms of magnitude, idiosyncratic shocks lead to an increase in mean hours spent on economic activities by 4.13 hours per week while covariate shocks lead to an increase in household activities by 0.11 hours (6.6 minutes) per day on average, conditional on controlling for other factors. Interestingly, the results show that the impact of idiosyncratic shocks is stronger than the effect of covariate shocks.

These results can be driven by several transmission channels since the effects of shocks on children's outcomes can be both of pecuniary and non-pecuniary nature. The effect of shocks can be mediated through a fall in household income (say, due to a fall in production when hit by covariate shocks or an increase in health expenditure when faced with idiosyncratic shocks) or a decline in adult labor that may lead to a need for the child labor to replace the sick/dead household member. The finding is consistent with results from the existing literature on shocks and children's outcomes. Beegle et al. (2006) also show that child labor (children's time spent on non-market activities and domestic chores) significantly increase in response to shocks.

Heterogeneity in the effect of shocks based on sex of a child

Personal characteristics of children have implications on child labor. The statistically significant estimate on the variable for sex of a child suggests difference in hours of work between boys and girls (see Table 3.3). The positive sign for the sex dummy in the regression for weekly hours of economic work denotes that boys are more likely to involve in economic activities and spend about 6.58 weekly hours more than girls on average. On the other hand, the negative sign for sex dummy in the regression for daily hours of housework implies that girls spend more time collecting firewood and fetching water; girls spend about 0.5 hours (30 minutes) a day more than boys on average in household work. This provides evidence for the existence of gender differences in tasks, which are particularly relevant if shocks affect the marginal product of labor in certain activities.

It is worth investigating whether the aforementioned gender differences in child work (also implied by the descriptive analysis) lead to asymmetries in the estimated effects of shocks and other determinants of child work. Accordingly, a gender disaggregated analysis is run in order to test if estimated results are homogenous for boys versus girls (see Table 3.4).

Table 3.4: Estimation results for child work in different rural activities, disaggregated by sex

	BOYS		GIRLS	
	Weekly hours spent on economic activities	Daily hours spent on household activities	Weekly hours spent on economic activities	Daily hours spent on household activities
Idiosyncratic_shocks	0.412 (2.91)	-0.052 (0.14)	5.746** (2.26)	0.403** (0.17)
Covariate_shocks	0.606 (0.92)	0.059 (0.04)	1.466* (0.78)	0.140** (0.06)
Age of child	0.764*** (0.17)	0.036*** (0.01)	0.320** (0.15)	0.096*** (0.01)
Biological_child	-1.781 (1.65)	-0.005 (0.08)	-1.179 (1.54)	-0.300*** (0.11)
Male headed	-0.470 (1.52)	0.008 (0.07)	0.753 (1.23)	-0.066 (0.09)
Age of household head	-0.005 (0.04)	0.001 (0.00)	-0.047 (0.03)	0.001 (0.00)
Years of schooling of head	-0.146 (0.15)	0.008 (0.01)	-0.214* (0.13)	-0.007 (0.01)
No of infants(<6yrs)	0.256 (0.47)	0.003 (0.02)	-0.151 (0.40)	0.031 (0.03)
No of male adults	-1.671*** (0.42)	-0.038* (0.02)	-0.972*** (0.36)	-0.005 (0.03)
No of female adults	-0.742 (0.50)	-0.107*** (0.03)	-0.274 (0.41)	-0.178*** (0.03)
Landsize_percapita	1.851 (2.03)	0.119 (0.10)	0.314 (1.83)	-0.335** (0.14)
Livestock_holding	0.533*** (0.15)	-0.014 (0.01)	-0.099 (0.14)	-0.017 (0.01)
Log(Non-labor_income)	-0.258 (0.17)	0.006 (0.01)	-0.070 (0.16)	0.014 (0.01)
Credit_access	2.139*** (0.75)	-0.044 (0.04)	0.975 (0.67)	0.138*** (0.05)
Observations	2,745	2,745	2,436	2,436
<i>Left-censored observations</i>	<i>946</i>	<i>1,854</i>	<i>1,128</i>	<i>1,036</i>
<i>Uncensored observations</i>	<i>1,799</i>	<i>891</i>	<i>1,308</i>	<i>1,400</i>

Notes:

- The data source is LSMS-ISA (2011/12, 2013/14 and 2015/16), with restricted sample of children (7-17 years)
- Year and region effects are controlled for in all the regressions.
- Average marginal effects (dy/dx) are reported with robust standard errors in parentheses.
- *, **, *** indicate significance at 10%, 5% and 1%, respectively.

The results reported in Table 3.4 suggest the presence of substantial differences in the effect of shocks across boys and girls. According to the results, shocks significantly affect hours of work of only girls. Girls residing in households that faced idiosyncratic shocks spend, on average, about 5.75 weekly hours more on economic activities and 0.4 hours (24 minutes) more on daily household chores. Also, covariate shocks increase the mean time that girls spend in economic activities and household chores by about 1.47 hours a week and by 0.14 hours (8.44 minutes) a day, respectively.

The results from the gender disaggregated analysis also imply that girls' personal characteristics have stronger effects on the hours spent in household activities in comparison with boys. On the other hand, boys' personal characteristics have stronger effects on the hours spent on economic activities given they work.

Estimates of control variables do not have a causal interpretation. Yet estimates of some regressors suggest interesting patterns. For instance, the positive significant estimate of age of a child implies that hours of work increase with age of a child, probably because a child's productivity rises in age. The fact that both boys and girls work more when they grow older is worrying as it means that older children (probably, adolescents in upper school) are overburdened with work, relative to younger children. Another important feature of a child that has implications on child labor is the relationship of a child with the household head. Our results imply that biological children (son/daughter) work relatively less than other children in the household (children from earlier marriage and absent parents). This is true for housework where girls are mostly responsible. This result is similar to that of Haile and Haile (2007).

Although age and sex of household head does not seem to affect the involvement of boys and girls in any work, education level of the household head matters for child work in economic activities. Not surprisingly, we do find that higher education leads to lower child labor for all levels of education. Children (girls) from households with heads that attained higher years of schooling are found to work relatively less. This is because children of educated parents may not be as resource constrained as their counterparts from illiterate parents as education enhances earnings potential.

All of the household composition variables have statistically significant effects on child work except the number of infants (younger siblings). Household size (as measured by number of adult members of households) is associated with less hours of child work in all activities for both boys and girls. The negative impact of number of adult men in the household on economic work time is relatively higher for boys while the negative effect of number of adult women in the household on housework is higher for girls relative to boys. Children residing in labor endowed households work fewer hours and probably do better in school because the amount of work is shared among household members.

Land and livestock holding, which are the two most important productive resources that rural households own, have implications on child time allocation. According to the results reported in Table 3.4, per capita land holding is negatively associated with daily hours of housework for girls while livestock holding increases hours spent in economic activities for boys. This is to be expected as most boys in rural areas are responsible for herding.

Heterogeneity in the effect of shocks based on access to credit and non-labor income

Rural households differ in terms of asset holdings and wealth status. Furthermore, they have different access to finance. Such differences have direct implications on households' labor allocation decisions of rural households. Particularly, they have implications on child labor especially when there is a high degree of imperfection in the access to finance and in the adult labor market.

Access to finances, through borrowing or transfers, is assumed to ease liquidity constraints and raise household income and therefore help households overcome transitory shocks (Maldonado and González-Vega, 2008). In this regard, households' non-labor income and access to credit can be expected to mitigate the effect of shocks on child labor.

The aforementioned significant effect of shocks on child labor may be interpreted as evidence of incomplete credit and insurance markets. Hence, the second objective of this study is to probe this effect by interacting the shock indicators with the variables assumed to ease the effect of shocks (non-labor income and access to credit), whereby coefficients

of the interaction terms capture the differential impact of a shock among children from households with different levels of non-labor income and constraint to access to credit.

Table 3.5 reports part of the results for the heterogeneous effect of shocks based on household's non-labor income and access to credit. Most of the interaction terms have the expected negative signs (since the considered coping mechanisms are anticipated to ease the effect of shocks on child labor); however, none are significant at the conventional level for total number of children in our sample. But, further analysis disaggregated by sex and age group of the child yield significant results supporting the hypothesis that both household's non-labor income and access to credit buffer against shocks.

Table 3.5: Estimation results for heterogeneous effect of shocks on child work (hours of economic work)

	Total	Disaggregated by Sex		Disaggregated by Age		
		Boys	Girls	< 12 Years	12-14 Years	>14 Years
Shock indicators						
Idiosyncratic_shock	7.99** (3.82)	0.54 (5.27)	13.20** (5.36)	5.45 (5.14)	10.65* (6.29)	-2.63 (14.02)
Covariate_climate	2.46* (1.33)	2.52 (1.71)	2.88 (2.04)	4.11** (2.07)	4.59** (2.07)	-3.77 (2.84)
Household status indicators (coping mechanisms)						
Log(Nonlabor_income)	-0.11 (0.26)	-0.08 (0.31)	-0.14 (0.44)	-0.47 (0.39)	0.456 (0.41)	-0.73 (0.56)
Credit_access	2.94*** (1.02)	3.73*** (1.28)	1.98 (1.60)	3.94*** (1.47)	2.642* (1.60)	2.72 (2.47)
Interaction of shock with coping mechanisms						
Nonlabor_income* Idiosyncratic_shock	1.07 (1.65)	0.06 (2.08)	3.50 (2.64)	1.16 (1.97)	-0.127 (3.27)	0.00 (.)
Nonlabor_income* Covariate_shock	-0.57 (0.43)	-0.97* (0.53)	-0.20 (0.68)	-0.41 (0.68)	-1.052 (0.65)	0.16 (0.88)
Credit_access* Idiosyncratic_shock	-8.91 (8.68)	-0.28 (10.64)	-19.36 (14.56)	-20.01* (11.38)	6.958 (16.25)	47.65* (28.39)
Credit_access* Covariate_shock	-0.88 (2.16)	-2.31 (2.76)	1.49 (3.33)	-4.48 (3.39)	3.408 (3.32)	-8.12* (4.77)
Observations	5,181	2,745	2,436	2,592	1,804	785
Left-censored obs.	2,254	946	1,128	2,254	946	1,128
Uncensored obs.	2,927	1,799	1,308	2,927	1,799	1,308

Notes:

- The data source is LSMS-ISA (2011/12, 2013/14 and 2015/16), with restricted sample of children (7-17 years)
- Child and parent characteristics, household composition, year and region effects are controlled for in all regressions.
- Coefficients are reported with robust standard errors in parentheses.
- *, **, *** indicate significance at 10%, 5% and 1%, respectively.

As indicated in the gender disaggregated analysis, non-labor income eases the effect of covariate shocks on child labor only for boys. Although households' non-labor income is not found to affect hours of work at normal times, it negatively affects boys' weekly hours spent in economic activities when households face covariate shocks (see Table 3.5).

According to the result from age disaggregated analysis, there is a significant buffering effect of credit access for young children under the age of 12 years. That is, for households that are hit by covariate shocks, young children residing in households with credit access allocate relatively fewer weekly hours to economic works as compared to children from households with no credit access. Besides, it is important to note that (lack of) access to credit plays a central role in child labor as indicated by the significant coefficient for credit access. The positive coefficient shows that credit access significantly increases hours of child work at normal times. This finding points to imperfections in the adult labor market and household's inability to trade-off resources inter-temporally in an optimal way, both of which lead to child labor. Working children contribute to the current labor supply and earnings of a household, but at the cost of future earnings of the children.

3.6.2. Effect of child work on educational attainment

The main results from the previous section imply that shocks lead to increased hours of child work. Child work is widely perceived to impede the educational attainment of children, particularly if the intensity of working is very high. In this section, we check whether the amount of time spent working is likely to result in a trade-off with schooling of children. For this purpose, a mixed-effects Tobit regression model is fitted where the dependent variable is age-adjusted school outcome variable (grade-for-age (GAGE)).

The relevant results are presented in Table 3.6 below. Column (1) and (2) show the effect of child work while column (3) and (4) show the effect of child labor (that is, excessive hours of child work) on educational attainment. The fact that the dependent variable (grade-for-age (GAGE)) is an index and the variable of interest (hours of child work) is a latent variable precludes a straightforward interpretation of the estimates. Still, signs of estimates have implications on potential association between child work and educational attainment.

Table 3.6: Results from mixed-effects Tobit regressions for educational attainment

Dependent variable: grade-for-age(GAGE)	Effect of child work		Effect of child labor, controlling for endogeneity	
	(1)	(2)	(3)	(4)
Weekly hours spent on economic activities	0.087 (0.09)			
(Weekly hours spent on econ activities) ²	-0.005*** (0.00)			
Daily hours spent on household activities		3.652*** (1.26)		
(Daily hours spent on hh activities) ²		-0.600* (0.28)		
Child Labor for <12 years old (>4 daily hrs of hhwork / >0 weekly hrs of ecowork)			-0.267*** (0.07)	
Child Labor for >12 years old (>4 daily hrs of hhwork / >14 weekly hrs of ecowork)				-0.074** (0.03)
Predicted residual from the reduced form child labor equation for <12 years old			0.417* (0.23)	
Predicted residual from the reduced form child labor equation for >12 years old				-0.299* (0.11)
Observations	5,181	5,181	2,592	2,589
<i>Left-censored observations</i>	<i>1,556</i>	<i>1,556</i>	<i>1,115</i>	<i>441</i>
<i>Uncensored observations</i>	<i>3,625</i>	<i>3,625</i>	<i>1,477</i>	<i>2,148</i>

Notes:

- *The data source is LSMS-ISA (2011/12, 2013/14 and 2015/16), with the restricted sample of children (7-17 years).*
- *Other determinants of educational attainment, including year and region effects are controlled for in all regressions.*
- *Average marginal effects (dy/dx) are reported with robust standard errors in parentheses;*
- **, **, *** indicate significance at 10%, 5% and 1%, respectively.*
- *Columns (3) and (4) control for potential endogeneity of child labor through the CFA model estimation by including the predicted residual from the reduced form equation of the potentially endogenous variable (child labor) as extra regressors in the structural equation of educational attainment.*

Variables for hours of child work (hours of economic work/hours of housework) and their squares are included as regressors. The quadratic term is included in order to capture non-linear effects of hours worked. The variable for hours spent on economic work is not statistically significant, perhaps due to the fact that child work is endogenous as there may be unobserved factors correlated with child work and educational attainment. However, the quadratic term for hours of economic work is negative significant, supporting the proposition that excessive hours of economic work (beyond $\frac{0.087}{2(0.005)} = 8.7$ hours per week) have adverse marginal impacts on educational attainment (see column (1)).

On the other hand, both the estimates for hours of housework and its square are statistically significant at conventional levels, with opposing signs (see column (2)). The opposing signs imply an inverted U-shaped relationship between hours of child work and educational attainment. The marginal effects with respect to hours of housework suggest that housework has a positive impact on educational attainment from the very first hour of work, but beyond 3 hours a day, the marginal impact changes direction and excessive housework adversely affects educational attainment for all children. The optimal level of household activity is $\frac{3.652}{2(0.6)} = 3.04$ hours per day.

Overall, the results suggest that excessive hours of child work result in lower educational attainment. This finding is in line with previous empirical literature from Ethiopia that show an inverse association between child work and schooling (Haile and Haile, 2007).

The difference in the sign of child work hours and the square terms suggests that child work and child labor are not comparable; thus, analyzing the effect of child work and child labor (excessive child work) may yield different results. In order to analyze the effect of child labor on educational attainment, we consider UNICEF's criteria for identifying any given work as child labor. That is, for young children under 12 years, child labor is officially defined as child work in any economic activity or domestic chores beyond 4 hours per day (28 hours per week); while for children aged 12 years and more, child labor is defined as domestic chores in excess of 28 hours per week or income-generating work in excess of 14 hours per week.

Analyzing the effect of child labor based on the official definition did not bring different results (see column (3) and column (4)). That is, child labor has a negative impact on educational attainment of children, with relatively larger effect for young children under 12 years: an hour increase in hours of child work is translated into 0.267-unit reduction in the educational attainment index. Causality can be attached to the results since endogeneity of child labor is controlled by CFA approach through the inclusion of predicted residual from the reduced form equation. One can infer that there is clear causal evidence that child labor has an adverse impact on educational attainment.

3.7. Limitations and Robustness check

This study is limited in several aspects. Primarily, the analysis in this paper does not preclude the potential endogeneity of idiosyncratic shocks. Also, the analysis of the trade-off between child work and educational attainment does not fully control unobservable child characteristics that may in part explain educational attainment. Further work on eliminating this risk of endogeneity could improve precision of the estimated relationships. Better instruments (strong child level instruments) are needed in order to pick up more of the within household variation and to be able to disentangle the impact of child labor more precisely.

Another limitation is in the analysis considering only of observations with nonzero values, which does not control for sample selection. The bias due to sample selection may not be a serious problem in our study where about three-fourth of the children have non-zero hours of work. And the measure of educational attainment (GAGE) has observed zero values for less than 35 percent of children, thus sample selection into child employment does not have a significant impact on the work-schooling trade-off.

We run several sensitivity tests to verify the stability of our results. The estimated coefficients have proved to be very robust to several specifications and sample adjustments. First, analyzing the effect of shocks on child work on a narrower sample of children aged 7-15 years or on a wider sample of children aged 7-18 years did not bring any significant difference in the results. Second, as a sensitivity analysis, OLS regression is run considering the potential limitations of the Tobit model when estimating the effects of covariates on long-run time use. In terms of sign, the results from OLS regression are similar to the Tobit results. However, there is difference in magnitude: the coefficients from OLS regressions are lower than that of Tobit regressions. Overall, the results are sufficiently robust to suggest the assumed negative impact of shocks on child work and that of child labor on human capital accumulation.

3.8. Conclusion and policy implications

The aim of this study is to determine whether there is empirical evidence for the commonly made assumption that child work increases in response to shocks, and that excessive hours of child work adversely affect educational attainment of working school aged children in rural Ethiopia.

According to the empirical results, there is a significant increase in children's time spent on economic activities (agricultural and non-agricultural activities) in response to idiosyncratic shocks, and an increase in total hours of child work including household activities (fetching water and firewood) in response to covariate shocks. There is evidence of heterogeneity in the effect of shocks depending on both the category of shocks faced and the type of activity that children are involved in. Another avenue of heterogeneity is gender. The gender disaggregated analysis infer asymmetries in the effects of shocks resulting from the observed gender-based differences in the allocation of time. There is gender bias in child labor when households face shocks; only girls seem to experience harmful effects from both idiosyncratic and covariate shocks, in terms of increased hours of work.

In addition to shock indicators and child characteristics, other characteristics of households are also found to influence children's time allocation decisions. Higher literacy level of household heads and larger household size are found to discourage child work while livestock holding and access to credit intensify child work, especially for boys.

This study provides evidence for the heterogeneity in child labor across households with different levels of non-labor income and access to credit. The results of the study show that there is a significant buffering effect of non-labor income against idiosyncratic shocks on child labor hours for boys, but not for girls. The results also imply significant buffering effects of credit access. According to the results from the age disaggregated analysis, credit access helps households to lessen the pressure to rely on child labor when hit by idiosyncratic shocks for children aged 12-14 years while it eases the effect on child labor in case of covariate shocks for adolescents (14-17 years).

The paper provides strong statistical evidence on the adverse effect of child work on educational attainment, as measured by the age-adjusted school outcome variable – grade for age (GAGE). Analyzing the effect of child work based on official definition of child labor did not bring different results. That is, child labor (excessive hours of work) exhibits a negative effect on children’s educational attainment, with stronger negative effect for young children under 12 years.

The findings of the paper point to several policy implications. First, the significant effect of shocks on child labor points towards the need to design policies and interventions that would raise household income, enhance resilience, and empower households to withstand some of the shocks without resorting to child labor. For the case of the inherently risky agricultural sector, improved agricultural practices including development of small-scale irrigation systems as well as improved access to disease and drought resistant crop varieties could reduce the probability of occurrence of shocks and the magnitude of the subsequent adverse effects. Also, measures to improve the income-generating capacity of households (such as income diversification opportunities) could mitigate the effects of transitory income shocks.

Second, the observed gender biases in the effect of shocks and some coping strategies have important policy implications. Intervention programs need to be gender-sensitive in their design in order to have gender-equitable effects. In this regard, Ethiopia’s Productive Safety Net Programme (PSNP) is an exemplary social protection program that has a gender-sensitive protection approach. Also, promoting community-based awareness programs could play an effective role in eliminating such biases.

Third, findings of this paper point to possible mitigating measures as indicated by some buffering effects. Non-labor income and access to credit are found to buffer against shocks and reduce the use of child labor. This implies that improved access to credit and non-labor income, along with formal insurance schemes (such as social safety nets and other social protection schemes) could play an important role in reducing the adverse effects of transitory shocks on household income and help prevent households from having to rely on child labor as a coping strategy in the face of shocks.

Finally, the finding with respect to the second objective of this paper (that is, excessive child work exhibited a negative effect on children's educational achievement) has implications on reinforcing child labor reduction interventions with efforts to enforce and incentivize schooling of children, say by providing households with financial incentives to keep children in school (such as a cash transfer programme conditional on children attending school).

All in all, our results plea for a combination of properly designed policies in the areas of education, social protection, and labor markets. Policies that foster the smooth functioning of adult labor markets and help in curbing the demand for child labor, coupled with stronger enforcement of compulsory schooling for children are likely to be effective tools for reducing child labor.

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APPENDICES

Annex-I: Summary statistics

Table A.1. Definition of variables and descriptive statistics

Variable name	Definition
Dependent variables	
<i>Measure of hours of child work</i>	
Weekly_hrs_econ.work	Hours spent in any economic activity (agricultural and/or non-agriculture) during the last seven days
Daily_hrs_hh.work	Hours and minutes spent on household activities (fetching water and firewood) yesterday
<i>Measure of educational attainment</i>	
Schooling	Years of schooling of the child
Grade-for-Age (GAGE)	An index for educational attainment
	$GAGE = 100 * \left[\frac{\text{years of schooling of the child}}{\text{Age of the child} - 7} \right]$
Explanatory Variables	
<i>Variable of interest</i>	
Shock	Dummy=1 if household faced any shocks in the last 12 months; 0 otherwise
Idiosyncratic_shock	Dummy= 1 if household faced idiosyncratic shocks such as illness/death of member; 0 otherwise
Covariate_shock	Dummy=1 if household faced any covariate shocks such as flood/drought/ heavy rain; 0 otherwise
<i>Control variables</i>	
<i>Child characteristics</i>	
Boy	Sex of child dummy (=1 if boy; 0 if girl)
Age	Age of child
Biological_child	Relation to household head dummy (=1 if child is son/daughter)
<i>Parent characteristics and household composition</i>	
Male_head	Sex of the household head dummy (=1 if male headed)
Age_head	Age of the household head
Schooling_head	Years of schooling of household head
No of infants(<6yrs)	Number of infants in household (under six years)
No of male adults	Number of male adult members in household (15-65 years)
No of female adults	Number of female adult members in household (15-65 years)
<i>Households' wealth/status indicators and potential buffers against shock</i>	
field_size_hect	Land holding (hectares)
Livestock holding	Livestock holding in tropical livestock unit (TLU)
Nonlabor_income	Amount of unearned income
Credit_access	Dummy=1 if household had access to credit last 12 months
<i>Community characteristics</i>	
Distance to school	Proximity to school (measured in minutes: 0-120 minutes grouped into 7 categories)

Note: The data source is LSMS-ISA (2011/12, 2013/14 and 2015/16).

**Table A.2. Descriptive statistics of the variables used for the analysis
(Pooled Sample of 5,181 children)**

Variables	Obs.	Mean	Std. Dev.	Min	Max
Weekly_hrs_econ.work	5,181	13.25	17.263	0	70
Daily_hrs_hh.work	5,181	0.60	1.052	0	6
Schooling	5,181	2.35	2.225	0	10
Grade-for-Age (GAGE)	5,181	49.49	47.868	0	500
Shock	5,181	0.26	0.438	0	1
Idiosyncratic_shock	5,181	0.09	0.283	0	1
Covariate_shock	5,181	0.20	0.400	0	1
Boy	5,181	0.53	0.499	0	1
Age	5,181	11.68	26.000	0	17
Biological_child	5,181	0.95	0.228	0	1
Male_head	5,181	0.92	0.275	0	1
Age_head	5,181	47.01	11.675	18	97
Schooling_head	5,181	2.04	2.893	0	15
No of infants(<6yrs)	5,181	.73	0.898	0	5
No of male adults	5,181	1.64	0.987	0	7
No of female adults	5,181	1.55	0.832	0	7
field_size_hect	5,181	0.54	0.935	0	12.24
Livestock holding	5,181	1.17	2.370	0	38.5
Nonlabor_income	5,181	229.76	1981.900	0	42000
Credit_access	5,181	0.32	0.467	0	1
Distance to school	5,181	2.35	1.076	1	7

Note:

- All the statistics are based on the survey design weights included in the data.¹³
- In cases of measures of hours of child work and educational attainment, mean values are computed including the zero values).
- The data source is LSMS-ISA (2011/12, 2013/14 and 2015/16), with restricted sample of children aged 7-17 years.

¹³ The weighted sample has 10 strata with 54 Primary Sampling Units (PSUs), where there are different number of observations in each PSU and in each strata. There are 5,181 observations in the PSUs with a minimum of 3, a maximum of 585 and an average of 96 observations in the PSUs.

**Table A.3. Descriptive statistics of the variables used for the analysis
(Sub-samples based on shock experience)**

	Sub sample of children in households that had experienced a shock (1,451 children)		Sub sample of children in households that had not experienced a shock (3,730 children)	
	Mean	Std.Dev.	Mean	Std.Dev.
Weekly_hrs_econ.work	13.70	18.657	13.10	16.747
Daily_hrs_hh.work	0.71	1.255	0.57	0.968
Schooling	2.22	2.211	2.39	2.229
Grade-for-Age (GAGE)	44.70	46.612	51.17	48.193
Shock				
Idiosyncratic_shock	0.34	0.473		
Covariate_shock	0.77	0.420		
Boy	0.53	0.499	0.52	0.499
Age	11.997	2.655	11.57	2.57
Biological_child	0.96	0.199	0.94	0.237
Male_head	0.91	0.284	0.92	0.272
Age_head	48.50	11.943	46.49	11.527
Schooling_head	1.73	2.771	2.15	2.927
No of infants(<6yrs)	0.76	0.934	0.72	0.885
No of male adults	1.65	0.997	1.64	0.984
No of female adults	1.62	0.836	1.53	0.829
field_size_hec	0.56	1.013	0.53	0.906
Livestock holding	1.08	2.438	1.21	2.345
Nonlabor_income	315.22	1977.554	199.89	1982.790
Credit_access	0.35	0.479	0.31	0.462
Distance to school	2.4	1.126	2.33	1.083

Note:

- All the statistics are based on the survey design weights included in the data.
- In cases of measures of hours of child work and educational attainment, mean values are computed including the zero values).
- The data source is LSMS-ISA (2011/12, 2013/14 and 2015/16), with restricted sample of children aged 7-17 years.

Annex-II: Econometric estimations results

**Table B.1. Estimation results for child work in different rural activities
(hours spent in economic and household activities), disaggregated by sex**

	TOTAL		BOYS		GIRLS	
	Weekly hours spent on economic activities	Daily hours and minutes spent on household activities	Weekly hours spent on economic activities	Daily hours and minutes spent on household activities	Weekly hours spent on economic activities	Daily hours and minutes spent on household activities
Idiosyncratic_shock	4.127** (1.90)	0.172 (0.11)	0.412 (2.91)	-0.052 (0.14)	5.746** (2.26)	0.403** (0.17)
Covariate_shock	0.965 (0.62)	0.105*** (0.04)	0.606 (0.92)	0.059 (0.04)	1.466* (0.78)	0.140** (0.06)
Boy	6.581*** (0.49)	-0.499*** (0.03)				
Age of child	0.589*** (0.11)	0.060*** (0.01)	0.764*** (0.17)	0.036*** (0.01)	0.320** (0.15)	0.096*** (0.01)
Biological_child	-1.526 (1.15)	-0.146** (0.07)	-1.781 (1.65)	-0.005 (0.08)	-1.179 (1.54)	-0.300*** (0.11)
Male_head	0.208 (1.06)	-0.024 (0.06)	-0.470 (1.52)	0.008 (0.07)	0.753 (1.23)	-0.066 (0.09)
Age_head	-0.022 (0.03)	0.001 (0.00)	-0.005 (0.04)	0.001 (0.00)	-0.047 (0.03)	0.001 (0.00)
Schooling_head	-0.187* (0.11)	0.002 (0.01)	-0.146 (0.15)	0.008 (0.01)	-0.214* (0.13)	-0.007 (0.01)
No of infants(<6yrs)	0.136 (0.32)	0.013 (0.02)	0.256 (0.47)	0.003 (0.02)	-0.151 (0.40)	0.031 (0.03)
No of male adults	-1.278*** (0.29)	-0.032* (0.02)	-1.671*** (0.42)	-0.038* (0.02)	-0.972*** (0.36)	-0.005 (0.03)
No of female adults	-0.564* (0.33)	-0.127*** (0.02)	-0.742 (0.50)	-0.107*** (0.03)	-0.274 (0.41)	-0.178*** (0.03)
landsize_percapita	1.265 (1.41)	-0.076 (0.09)	1.851 (2.03)	0.119 (0.10)	0.314 (1.83)	-0.335** (0.14)
Livestock_holding	0.197* (0.10)	-0.015** (0.01)	0.533*** (0.15)	-0.014 (0.01)	-0.099 (0.14)	-0.017 (0.01)
Log(Nonlabor_income)	-0.167 (0.12)	0.009 (0.01)	-0.258 (0.17)	0.006 (0.01)	-0.070 (0.16)	0.014 (0.01)
Credit_access	1.515*** (0.52)	0.046 (0.03)	2.139*** (0.75)	-0.044 (0.04)	0.975 (0.67)	0.138*** (0.05)
Year dummies (relative to 2011)						
yr_2013	-1.358* (0.71)	-0.158*** (0.04)	0.472 (1.05)	-0.148*** (0.05)	-2.774*** (0.92)	-0.185*** (0.07)
yr_2015	-2.230*** (0.78)	-0.250*** (0.05)	-1.200 (1.17)	-0.249*** (0.06)	-2.677*** (1.01)	-0.262*** (0.08)
Region dummies						
Region_Tigray	4.733*** (1.26)	-0.004 (0.08)	7.403*** (1.77)	0.131 (0.09)	1.381 (1.54)	-0.209* (0.12)
Region_Amhara	5.691*** (0.99)	-0.008 (0.06)	7.776*** (1.39)	0.059 (0.07)	2.972** (1.21)	-0.109 (0.09)
Region_Oromia	0.766 (0.98)	0.066 (0.06)	1.302 (1.40)	0.074 (0.07)	-0.123 (1.14)	0.007 (0.09)
Region_SNNP	-2.739*** (0.95)	0.261*** (0.06)	-2.063 (1.34)	0.395*** (0.07)	-3.783*** (1.12)	0.005 (0.08)
Observations	5,181	5,181	2,745	2,745	2,436	2,436
<i>Left-censored observations</i>	2,254	2,890	946	1,854	1,128	1,036
<i>Uncensored observations</i>	2,927	2,291	1,799	891	1,308	1,400
<i>Log likelihood</i>	-15226.46	-6362.2	-9093.59	-2807.56	-6130.05	-3499.97
<i>LR test vs. Tobit model</i>						
<i>chibar2(01)</i>	185.43	201.00	94.44	98.47	59.35	69.78
<i>Prob > chibar2</i>	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table B.2. Estimation results for heterogeneous effect of shocks on child work (hrs in econ activities)

	TOTAL	DISAGGREGATED BY SEX		DISAGGREGATED BY AGE		
		BOY	GIRL	< 12 YEARS	12-14 YEARS	>14 YEARS
Idiosyncratic_shocks	7.992** (3.82)	0.537 (5.27)	13.199** (5.36)	5.451 (5.14)	10.651* (6.29)	-2.625 (14.02)
Covariate_shocks	2.462* (1.33)	2.517 (1.71)	2.877 (2.04)	4.110** (2.07)	4.594** (2.07)	-3.769 (2.84)
Sex dummy (=1 if boy)	11.529*** (0.86)			10.323*** (1.25)	11.682*** (1.34)	13.021*** (2.53)
Age of child	1.027*** (0.19)	0.161*** (0.26)	0.687** (0.32)	1.378*** (0.48)	0.191 (0.76)	1.094 (1.27)
Biological_child	-2.453 (2.03)	-2.537 (2.53)	-1.899 (3.32)	-4.526 (3.00)	-0.753 (3.09)	-3.078 (4.26)
Sex dummy (=1 if male headed)	0.284 (1.85)	-0.869 (2.32)	1.481 (2.64)	-2.504 (2.53)	3.296 (2.57)	1.667 (3.68)
Age of household head	-0.040 (0.05)	-0.009 (0.06)	-0.101 (0.07)	-0.058 (0.07)	-0.046 (0.07)	-0.058 (0.10)
Years of schooling of head	-0.332* (0.19)	-0.220 (0.23)	-0.466* (0.28)	-0.486* (0.26)	-0.218 (0.26)	0.161 (0.38)
No of infants(<6yrs)	0.249 (0.56)	0.447 (0.71)	-0.345 (0.86)	0.482 (0.84)	-1.338 (0.83)	0.646 (1.21)
No of male adults	-2.238*** (0.51)	-2.544*** (0.64)	-2.065*** (0.77)	-2.953*** (0.80)	-2.478*** (0.73)	-0.692 (1.05)
No of female adults	-0.973* (0.59)	-1.157 (0.76)	-0.541 (0.87)	-0.230 (0.93)	-1.486* (0.83)	-0.340 (1.27)
Landsize_percapita	2.169 (2.47)	2.809 (3.09)	0.625 (3.91)	6.826* (3.52)	-1.236 (3.55)	-10.757 (9.40)
Livestock_holding	0.352* (0.18)	0.827*** (0.23)	-0.232 (0.29)	0.442* (0.25)	0.351 (0.29)	-0.435 (0.98)
Log(Nonlabor_income)	-0.114 (0.26)	-0.078 (0.31)	-0.136 (0.44)	-0.470 (0.39)	0.456 (0.41)	-0.729 (0.56)
Credit_access	2.935*** (1.02)	3.728*** (1.28)	1.977 (1.60)	3.940*** (1.47)	2.642* (1.60)	2.717 (2.47)
<i>Interaction of shock with coping mechanisms</i>						
Nonlabor_income*	1.065 (1.65)	0.057 (2.08)	3.503 (2.64)	1.159 (1.97)	-0.127 (3.27)	0.000 (.)
Nonlabor_income* Covariate_shock	-0.566 (0.43)	-0.969* (0.53)	-0.202 (0.68)	-0.412 (0.68)	-1.052 (0.65)	0.162 (0.88)
Credit_access* Idiosyncratic_shock	-8.907 (8.68)	-0.275 (10.64)	-19.355 (14.56)	-20.009* (11.38)	6.958 (16.25)	47.652* (28.39)
Credit_access* Covariate_shock	-0.883 (2.16)	-2.313 (2.76)	1.486 (3.33)	-4.483 (3.39)	3.408 (3.32)	-8.118* (4.77)
<i>Year dummies (relative to 2011)</i>						
yr_2013	-2.319* (1.25)	0.777 (1.61)	-5.911*** (1.96)	-1.038 (1.75)	-4.132** (2.04)	-3.793 (6.35)
yr_2015	-3.829*** (1.37)	-1.770 (0.18)	-5.717*** (2.16)	-0.567 (2.17)	-5.943*** (2.04)	-4.992 (6.27)
<i>Region dummies</i>						
Region_Tigray	8.344*** (2.21)	11.441*** (2.70)	2.879 (3.30)	8.349*** (2.92)	12.649*** (3.07)	1.760 (4.27)
Region_Amhara	9.922*** (1.74)	11.839*** (2.12)	-0.188 (2.60)	10.578*** (2.32)	11.982*** (2.43)	0.128 (3.57)
Region_Oromia	1.367 (1.72)	1.931 (2.13)	-0.286 (2.44)	3.086 (2.24)	4.371* (2.41)	-13.280*** (3.65)
Region_SNNP	-4.846*** (1.66)	-3.245 (2.04)	-8.133*** (2.41)	-4.160* (2.19)	-2.525 (2.33)	-14.890*** (3.46)
Constant	-4.921 (3.95)	1.301 (4.95)	4.391 (6.13)	-5.094 (6.37)	3.195 (10.82)	1.105 (21.76)

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Table B2. – Continued from previous page

	TOTAL	DISAGGREGATED BY SEX		DISAGGREGATED BY AGE		
		BOY	GIRL	< 12 YEARS	12-14 YEARS	>14 YEARS
var(_cons[househol~)	117.513*** (12.46)	112.750*** (15.69)	123.502*** (20.67)	141.409*** (21.73)	80.312*** (29.61)	143.557*** (47.60)
var(_cons[househol~a	0.000 (0.00)	0.000 (0.00)	0.000 (0.00)	0.000 (0.00)	20.965 (40.00)	0.000 (0.00)
var(e.total_weekly~)	563.784*** (17.44)	526.863*** (21.11)	609.984*** (31.59)	590.365*** (28.36)	516.418*** (38.44)	451.847*** (51.44)
<i>Observations</i>	5,181	2,745	2,436	2,592	1,804	785
<i>Left-censored observations</i>	2,254	946	1,128	1,185	736	333
<i>Uncensored observations</i>	2,927	1,799	1,308	1,407	1,068	452
<i>Log likelihood</i>	-15224.53	-9093.59	-6130.05	-7428.95	-5476.13	-2314.91
<i>LR test vs. Tobit model</i>						
<i>chibar2(01)</i>	182.03	94.44	59.35	63.95	16.79	9.85
<i>Prob >= chibar2</i>	0.0000	0.0000	0.0000			

Table B.3. Results from mixed-effects Tobit regressions for educational attainment

Dependent variable: grade-for-age (GAGE)				
	(1)	(2)	(3)	(4)
Explanatory variables				
<i>Measures of child work</i>				
Weekly hours spent on economic activities	0.087 (0.09)			
(Weekly hours spent on econ activities) squared	-0.005*** (0.00)			
Daily hours spent on household activities		3.652*** (1.26)		
(Daily hours spent on hh activities) squared		-0.600* (0.28)		
<i>Measures of child labor with controls for endogeneity</i>				
Child Labor for < 12 years old (>4 daily hours of housework or >0 weekly hours of eco. work)			-0.267*** (0.07)	
Child Labor for >12 years old (>4 daily hours of housework or >14 weekly hours of economic work)				-0.074** (0.03)
Predicted residual from the reduced form child labor equation for <12 years old			0.417* (0.23)	
Predicted residual from the reduced form child labor equation for >12 years old				-0.299* (0.11)
<i>Control variables</i>				
Sex dummy (=1 if boy)	-1.209 (1.73)	-1.052 (1.75)	-4.301 (3.29)	1.263 (2.24)
Age of child	-1.519*** (0.37)	-1.662*** (0.37)	4.141*** (0.99)	-2.463*** (0.43)
Biological_child	10.514*** (3.66)	10.883*** (3.66)	12.596** (6.24)	5.655* (3.368)
Male headed	-3.039 (3.73)	-2.868 (3.74)	-3.997 (5.48)	1.91 (3.436)
Age of household head	0.096 (0.09)	0.090 (0.09)	0.262* (0.14)	-0.097 (0.09)
Years of schooling of head	1.313*** (0.32)	1.317*** (0.32)	2.053*** (0.52)	1.517*** (0.29)
No of infants(<6yrs)	-0.065 (0.83)	-0.189 (0.83)	-0.875 (1.51)	-1.725** (1.05)
No of male adults	-1.020 (0.83)	-0.882 (0.83)	1.641 (1.67)	-2.580*** (0.74)
No of female adults	-0.978 (0.91)	-0.702 (0.91)	-0.474 (1.79)	-0.632 (0.76)
Landsize_percapita	0.433 (3.68)	-0.132 (3.69)	4.775 (6.62)	-3.498 (3.22)
Livestock_holding	-0.282 (0.28)	-0.302 (0.28)	-0.879* (0.52)	0.309 (0.29)
Log(Nonlabor_income)	-0.015 (0.30)	-0.008 (0.30)	0.001 (0.58)	0.256 (0.25)
Credit_access	-0.337 (1.33)	-0.552 (1.33)	-2.247 (2.61)	1.451 (1.25)
Distance to nearest school	-5.511*** (0.57)	-5.630*** (0.57)	-9.970*** (1.04)	-0.888* (0.49)

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Table B3. – *Continued from previous page*

	(1)	(2)	(3)	(4)
<i>Year dummies (relative to 2011)</i>				
yr_2013	16.252*** (1.79)	16.364*** (1.79)	11.779*** (3.21)	12.796*** (1.84)
yr_2015	24.379*** (2.08)	24.824*** (2.09)	22.16*** (4.03)	18.762*** (2.15)
<i>Region dummies</i>				
Region_Tigray	16.484*** (4.54)	16.012*** (4.55)	8.721 *** (6.49)	27.897 *** (4.35)
Region_Amhara	8.93** (3.54)	8.846** (3.55)	2.99*** (5.32)	17.371*** (3.44)
Region_Oromia	-4.106 (3.47)	-3.667 (3.48)	-12.584 (4.84)	2.658 (3.29)
Region_SNNP	-3.109 (3.35)	-2.545 (3.37)	-11.878 (4.80)	2.745 (3.38)
Observations	5,181	5,181	2,592	2,589
<i>Left-censored observations</i>	1,556	1,556	1,115	441
<i>Uncensored observations</i>	3,625	3,625	1,477	2,148
<i>Log likelihood</i>	-20938.61	-20949.074	-9366.31	-10909.97
<i>LR test vs. Tobit model</i>				
<i>chi2(2)</i>	1042.87	1059.35	268.56	878.33
<i>Prob >= chibar2</i>	0.0000	0.0000	0.0000	0.0000

CHAPTER FOUR

DOES RURAL NON-FARM EMPLOYMENT DIVERSIFICATION IMPROVE HOUSEHOLD WELFARE?

Abstract

This study evaluates the impact of non-farm work participation on welfare of farm household in rural Ethiopia using the Endogenous Switching Regression (ESR) estimation technique on panel data in a correlated random effects framework. ESR helps in estimating the true welfare effect of non-farm work accounting for potential selectivity and endogeneity biases. We find non-farm work participant households to be systematically different from non-participant households in terms of socioeconomic and demographic characteristics, thus justifying the empirical method used in this study that controls for structural differences between groups. Empirical results suggest that households participating in non-farm activities in addition to farming have greater mean consumption compared to households engaged solely in farming, even after controlling for all confounding factors. The results from this study confirm the potential role of non-farm sector in improving welfare of farm households in rural areas of developing countries. Therefore, considerable policy attention should be given to non-farm activities as an important livelihood strategy of farm households and the necessary support should be in place to facilitate the participation of the disadvantaged households in rural Ethiopia (such as the land-poor and credit constrained households).

Keywords: Rural non-farm employment (RNFE) diversification, Rural Ethiopia, Welfare

JEL Codes: J22, J43, Q12

4.1. Introduction

The rural economy is not confined to agriculture, but it also includes other activities that relate to employment, income and livelihoods not directly derived from crop and livestock production. There has been an increasing recognition that non-farm income generating activities are important for rural households to diversify income sources and enhance livelihood opportunities (Bezu *et al.*, 2012; Olugbire *et al.*, 2011; Scharf and Rahut 2014; Shehu and Siddique, 2014).

Participation in non-farm activities is a major decision that has implications on welfare of households in many developing countries. Particularly, for rural households that depend on agriculture as their main source of employment, the extra income from non-farm activities increases average household income and consumption; thus, exerting a positive effect on household welfare (Osarfo *et al.*, 2016; Owusu *et al.*, 2011; Seng, 2015; Zereyesus *et al.*, 2017).

In the specific context of Ethiopia, agriculture remains a major source of employment and income; yet it is by no means the sole activity of rural households. Farm households in many parts of the country have been motivated to diversify their livelihoods by participating in a variety of non-agricultural activities in the form of self-employment and wage employment (Woldegabriel, 2016).

The underlying hypothesis of this study is that farm households that diversify into non-farm employment will be better off, in terms of welfare (as measured by household consumption), compared to if they would rely solely on farming. Against this backdrop, the study addresses the following research question: Does participation in non-farm activities in addition to farming contribute to improving welfare of households in rural Ethiopia? If so, what are the contributions, in terms of welfare gains/losses?

This paper endeavors to empirically investigate the effect of non-farm work on welfare of farm households in rural Ethiopia using nationally representative household level panel data constructed from the first three rounds of Ethiopian Socio-Economic Survey (ESS) (2011/12, 2013/14 and 2015/16).

The analysis is done in three steps. First, we identify factors that influence the decision of farm households to participate in non-farm activities in addition to farming. Second, we examine whether diversifying into non-farm activities is an effective strategy for improving welfare of farm households. Finally, we quantify the actual contribution of non-farm activities in improving welfare of farm households, in terms of welfare gains or losses, using an unbiased and consistent estimation of the treatment effects of such activities.

Much of the research on rural employment in developing countries has focused only on farm work disregarding the growth in non-farm activities in household livelihood in many of these countries. Yet, devising effective development policies aimed at improving rural livelihoods requires looking beyond agriculture and giving concomitant attention to non-agricultural activities in rural areas. There is limited research undertaken on the contribution of non-farm activities and their potentially important role in improving rural livelihoods in developing countries. Particularly in the Ethiopian context, there is paucity of documented information regarding non-farm activities. Not much is known about such activities and their role in improving household welfare, particularly among rural farmers in Ethiopia.

There are few studies from developing countries that look into the impact of working outside the farm on household welfare (Akaakohol and Aye 2014; Bezu *et al.*, 2012; Jabo *et al.*, 2014; Olugbire *et al.*, 2011; Osarfo *et al.*, 2016; Seng, 2015; Owusu *et al.*, 2011; Shehu and Siddique, 2014; Woldegabriel 2016; Zereyesus *et al.*, 2017). However, previous studies mostly use regional or village-specific data, not nationally representative data, hence limit broader applicability.

This study contributes to the broader literature on rural livelihood strategies by providing evidence on the factors influencing non-farm work participation and the effect of such an endeavor on welfare of farm households in rural Ethiopia. Particularly, ascertaining the welfare enhancing role of non-farm work participation by quantifying the effect of Rural Non-Farm Employment (RNFE) on consumption expenditure is helpful to inform policy makers on ways to improve rural livelihoods in Ethiopia and other developing countries.

A combination of econometric approaches is used to explore linkages between non-farm activities and household welfare in rural Ethiopia. An Endogenous Switching Regression (ESR) model is used to identify the causal impact of RNFE on rural household welfare. The model is appropriate as it controls for structural differences between RNFE participants and non-participants and accounts for selection bias. It also addresses the potential endogenous bias of non-farm work participation arising from unobserved factors that potentially determine both non-farm participation decision and welfare of the households.

Estimation of the two-stage ESR is done based on correlated random effects (CRE) framework, dealing effectively with time-invariant heterogeneity. CRE estimation enables to control for unobserved household characteristics that may correlate with RNFE participation decisions of rural households by using the Mundlak–Chamberlain device with household-level time averages as additional controls. Chamberlain–Mundlak device allows heterogeneity to be correlated with the time-varying explanatory variables.

The paper unfolds by providing a brief literature review in section two. Section three presents the empirical strategy used to effectively address the objectives of this study. Section four discusses the data and variables of interest for the analysis. Results of the analysis are presented in section five starting with descriptive statistics of the variables used in the regression analysis disaggregated by welfare regime of the household, and then delves into the treatment effects of diversification on household welfare. The last section concludes and presents the policy implications of this study's results.

4.2. Review of relevant literature

Several studies from developing countries have investigated the role of non-farm activities in improving welfare of farm households by analyzing the impacts on farming practice, household expenditure or household incomes (Akaakohol and Aye 2014; Bezu *et al.*, 2012; de Janvry and Sadoulet 2001; de Janvry, Sadoulet, and Zhu 2005; Jabo *et al.*, 2014; Olugbire *et al.*, 2011; Osarfo *et al.*, 2016; Owusu *et al.*, 2011; Scharf and Rahut 2014; Seng, 2015; Shehu and Siddique, 2014; Woldegabriel 2016; Zereyesus *et al.*, 2017).

Findings of these studies suggest that non-farm employment can spur household incomes, improve food security and substantially contribute to alleviating the severity of poverty among rural households (de Janvry, Sadoulet, and Zhu 2005; Lanjouw and Lanjouw, 2001; Lanjouw and Shariff, 2004; Owusu *et al.*, 2011).

The existing literature alludes to various ways through which non-farm activities affect household welfare and rural livelihoods positively. First, such activities predominantly create employment avenues for family members and help rural households with limited agricultural resources to employ their labor hours efficiently (Tafesse *et al.*, 2015). The non-farm sector plays an important role in rural development in terms of promoting job creation, mitigating rural unemployment and underemployment and slowing the push-driven rural-urban migration (Lanjouw and Lanjouw, 2001; Reardon *et al.*, 2007). The non-farm sector helps to absorb the surplus labor in rural areas of most developing countries by providing alternative employment opportunities to the growing rural labor force that cannot be employed in the agricultural sector (Lanjouw and Lanjouw, 1995).

Second, employment opportunities outside agriculture appear to be an additional source of income for rural households. Many empirical studies support the contribution of non-farm employment diversification in increasing household earnings and show that farm households that engage in non-farm employment tend to enjoy higher household income and greater consumption (Akaakohol and Aye, 2014; Barrett *et al.*, 2001; Block and Webb, 2001; de Janvry and Sadoulet, 2001; de Janvry, Sadoulet, and Zhu, 2005; Reardon, *et al.*, 1992; Scharf and Rahut, 2014; Seng, 2015).

Income earned from non-farm activities can also be used to invest in human capital, through education and health expenditures and thereby enhance household welfare. Besides, non-farm income provides households with income security, allows for purchase of productive inputs, and the liquidity to invest in more lucrative income generating non-agricultural activities (de Janvry *et al.*, 2005). Several studies across developing countries suggest the vital role of non-farm activities in improving farming practice. Income earned from non-farm activities allows households to spend more on agricultural inputs and produce agricultural products more efficiently (Anang, 2017; Lanjouw and Lanjouw, 2001;

Woldehanna and Oskam, 2001). On the other hand, non-farm activities require the transfer of labor out of farming (or at least a drop-in time spent on farming activities) and place constraints on other resources for farm operations; thus, may decrease farm productivity (Anang, 2017).

Third, participation in non-farm activities has been identified as one strategy that farm households use to diversify their earnings portfolio. Employment opportunities outside agriculture provide an additional source of income that contribute significantly to the survival strategies of households in developing countries (de Janvry and Sadoulet, 2001; Barrett et al., 2001). Rural Non-Farm Employment (RNFE) serves as a form of self-insurance mechanism against external shocks and other threats of farming (such as seasonality, climatic uncertainty, and diseases). The extra income from such employment helps to buffering the shock-induced farm income fluctuations, lessen the risk associated with intra-year food production, stabilize food consumption, sustain income, and reduce vulnerability (Barrett et al., 2001; Dimova and Sen, 2010; Ellis, 1998; Lanjouw and Lanjouw, 1995; Reardon et al., 2007; Reardon et al., 1992). RNFE is also noted to play an important role in tackling food insecurity in many rural areas of developing countries (Anang, 2017).

Most of the studies from Africa show that participation in rural non-farm employment (RNFE) is positively correlated with household welfare indicators such as wealth, income, consumption, and food security. For instance, Owusu *et al.* (2011) show the importance of non-farm employment for improving the living standards and poverty reduction in rural communities in Northern region of Ghana, where there is low productivity of agriculture resulting from poor agro-ecological conditions. The authors empirically examined the impact of non-farm activity on household income and food security. They found that farm households' engagement in non-farm employment has a positive and statistically significant effect on both household income and food security. Similar findings were obtained by Osarfo *et al.* (2016) and Zereyesus *et al.* (2017) in different regions of Ghana. Also, Akaakohol and Aye (2014) found that non-farm activities have significant positive impacts on household consumption expenditure in Nigeria. Similar result is reported by Jabo et al. (2014) for rural households in Nigeria.

Only few studies from Ethiopia attempt to look into the relationship between non-farm employment and household welfare. Bezu *et al.* (2012) examine whether RNFE leads to higher consumption expenditure growth in Ethiopia. They find a strong positive relationship between household's non-farm income share and expenditure growth. Similarly, Woldegabriel (2016) reports a positive impact of non-farm income on rural households' welfare with an inequality reducing effect.

4.3. Empirical strategy

A number of confounding factors complicate the identification of a causal relationship between employment diversification and welfare. From an econometric standpoint, the analysis may be affected by unobserved factors. Since household welfare and RNFE participation decisions could be influenced by household characteristics which are not captured in a survey data, unobserved heterogeneity can lead to measurement errors and biased estimation.

Furthermore, evaluation of the effects of non-farm activities on farm households' welfare is difficult due to econometric challenges such as endogeneity problems and self-selection bias. Participation into RNFE is hardly a random process because households with certain characteristics might self-select themselves in the decision of RNFE participation. For instance, households that are wealthier or more resourceful to begin with may be more inclined to participate in non-farm activities rather than RNFE in itself leading to higher levels of wealth. This can be controlled using asset and other wealth indicators as explanatory variables.

Failure to address the selection bias and failure to distinguish between the causal effect of RNFE and the effect of unobserved heterogeneity could lead to biased estimates and give rise to misleading policy implications. To properly evaluate the potential of non-farm activities to improve households' welfare, one needs unbiased and consistent estimates of the effects of such activities. In this regard, only few empirical studies try to evaluate the impacts of participation in non-farm activities on farm households' welfare by addressing

the endogenous bias of the RNFE participation decision and the inherent differences between RNFE participants and the non-participants.

Although empirical literature affirms self-selection of households into RNFE, only few studies have analyzed the impact of RNFE participation on household welfare accounting for selectivity bias that may occur as a result of unobservable factors (see Jabo *et al.*, 2014; Shehu and Siddique, 2014; Owusu *et al.*, 2011).

Few studies adopt parametric methods such as Heckman selection approach or standard treatment effect model to control for non-random sample selection. Yet, results from such models may be biased and inconsistent because they assume uniform impacts across different subsamples and hide the inherent interaction between the participation decision and factors affecting household consumption. The models cannot control for potential inherent systematic differences between RNFE participants and non-participants. That is, the structure of household expenditure would very likely be systematically different, especially if factors influencing the participation decision equally affect the consumption expenditure (Seng, 2015).

Some other studies attempt to account for the potential selection bias by employing non-parametric or semi-parametric statistical methods such as propensity score matching (PSM) where the well-being of RNFE participant households is compared with counterfactual groups of non-participant households. For example, Owusu *et al.* (2011) controls for potential selection bias based on PSM approach that allows to compare the income and food security of RNFE participants with those of non-participants. Osarfo *et al.* (2016) and Olugbire *et al.* (2011) use similar methodology to analyze the effect of participation in non-farm work on household income and food security in Ghana and Nigeria, respectively.

The PSM approach controls for biases that may arise from observables and accounts for systematic differences based on observed characteristics. However, the approach does not control for unobserved confounders (such as entrepreneurial skill, mental and physical capabilities, motivation, and wealth) that potentially influence both the treatment (the

decision of whether to engage in non-farm activities) and the outcome (household consumption as a proxy for well-being), making it difficult to infer a causal relationship between RNFE and well-being (Seng, 2015). In other words, a limitation of the PSM approach is that evaluation of the effects is carried out only with observed characteristics, whereas there might be systematic differences in characteristics of households that solely engage in farming and those that diversify into non-farm activities to supplement their livelihoods (Anang, 2017). For instance, farm households that participate in non-farm activities might be more hard-working than those who did not participate due to self-selection. As a result, one might notice a significantly higher welfare among those who participate in non-farm activities. Neglecting these effects is likely to give a false picture of the relative welfare status among participant and non-participant households, thus, it may result in biased and inconsistent estimates.

This study adopts an Endogenous Switching Regression (ESR) model to address the above-mentioned econometric challenges. The ESR model allows tests of assumptions about the exogeneity of treatment effects from survey data. It aims to reduce the bias and inconsistency of the estimations by controlling for selection bias due to observed and unobserved characteristics of households and systematic differences between participants and non-participants.

Other researchers have also used the ESR approach to address endogeneity and sample-selection bias. Dedehouanou *et al.* (2015) utilized endogenous switching regression approach to assess the effect of off-farm self-employment on agricultural expenditure and food security in Niger. Seng (2015) used a similar method to analyze the effects of diversifying into off-farm activities on farm households' welfare in terms of household food consumption in rural Cambodia. Anang (2017) also used endogenous switching regression model to address selection into non-farm work, and to measure the effect of participation on productivity of smallholder farm households in northern Ghana.

Endogenous Switching Regression (ESR)

In this study, following Lokshin and Sajaia (2004), we employ a two-step ESR approach to examine the factors that influence household's decision to participate in non-farm work and the impact of participation on household consumption.

The first step of the ESR model is specified as follows:

$$\text{RNFE}^* = \alpha z' + \mu ; \quad \text{RNFE} = \begin{cases} 1 & \text{if } \text{RNFE}^* > 0 \\ 0 & \text{otherwise} \end{cases} \quad (4.1)$$

Equation (4.1) states the selection model into participation in rural non-farm work. It specifies the binary choice of households to participate in non-farm work conditioned on observed covariates. RNFE^* is a latent dependent variable for participation in non-farm activity, which is observed through a farm household's choice to participate in non-farm work. The dependent variable, RNFE , is a binary indicator of the '*treatment*' which equals to 1 for a farm household participates in any non-farm activity (that is, household with any member that engages in at least one non-farm work in addition to its primary farm work), and 0 otherwise.

z' is the vector of covariates for the selection model such as household demographic characteristics, physical and financial endowments of the households, social capital proxies of the household and other variables that influence the likelihood of engaging in non-farm activities. α is a vector of unknown parameters, and μ is a random error term.

Equations (4.2a) and (4.2b) specify the second step of the ESR model treating participation and non-participation as regimes. That is, the household consumption functions conditional on the two regimes or decision states (whether or not to participate in non-farm work) are written in an endogenous switching regression regime model.

$$\text{Participants:} \quad Y_1 = \beta_1 x_1 + \varepsilon_1 \quad \text{if} \quad \text{RNFE} = 1 \quad (4.2a)$$

$$\text{Non-participants:} \quad Y_0 = \beta_0 x_0 + \varepsilon_0 \quad \text{if} \quad \text{RNFE} = 0 \quad (4.2b)$$

Y_1 and Y_0 are the outcome indicator variables of household consumption for participant and non-participant households respectively; β_1 and β_0 are vectors of parameters to be estimated; x_1 and x_0 are the observed vectors of covariates determining household consumption for participant and non-participant, respectively. Although the variable sets z and x can overlap, there must be at least one variable in z that does not appear in x to properly identify the outcome equations. That is, we need selection instruments that directly determine the decision to engage in non-farm activities (the endogenous selection variable) but not household welfare indicators such as consumption.

Finally, the stochastic error terms $(\mu, \varepsilon_1, \varepsilon_0)$ are assumed to follow a trivariate normal distribution, with zero mean and non-singular covariance matrix expressed as:

$$cov(\mu, \varepsilon_1, \varepsilon_0) = \begin{bmatrix} \sigma_{\varepsilon_1}^2 & \sigma_{\varepsilon_1\varepsilon_0} & \sigma_{\varepsilon_1\mu} \\ \sigma_{\varepsilon_0\varepsilon_1} & \sigma_{\varepsilon_0}^2 & \sigma_{\varepsilon_0\mu} \\ \sigma_{\mu\varepsilon_1} & \sigma_{\mu\varepsilon_0} & \sigma_{\mu}^2 \end{bmatrix} \quad (4.3)$$

Variance of the error term in the selection equation, $var(\mu) = \sigma_{\mu}^2$, is assumed to be one; variances of error terms in the outcome equations are $var(\varepsilon_1) = \sigma_{\varepsilon_1}^2$ and $var(\varepsilon_0) = \sigma_{\varepsilon_0}^2$. The covariances are $cov(\varepsilon_1, \varepsilon_0) = \sigma_{\varepsilon_1\varepsilon_0}$, $cov(\varepsilon_1, \mu) = \sigma_{\varepsilon_1\mu}$, and $cov(\varepsilon_0, \mu) = \sigma_{\varepsilon_0\mu}$. Symmetry of the covariances in the upper and lower triangles of the covariance matrix (4.3) is assumed.

The ESR model can be estimated by using a two-stage procedure when the error terms of either of the welfare outcome equations are correlated with the error of the selection equation (because there are unobservable factors associated with selection bias). In the first stage, a probit model of regime choice is estimated to identify factors that influence rural households' decision to participate in non-farm activities. And we predict the Inverse Mills Ratios (IMRs) at z_{α} for participants and non-participants, respectively as follows:

$$\lambda_1 = \frac{\phi(z_{\alpha})}{\Phi(z_{\alpha})_{it}} \quad (4.4a)$$

$$\lambda_0 = \frac{-\phi(z_{\alpha})}{1-\Phi(z_{\alpha})} \quad (4.4b)$$

where ϕ is the standard normal probability density function and Φ is the cumulative distribution function of the standard normal distribution.

In the second stage, the outcome equations are estimated by including the predicted IMRs as regressors to yield following sets of equations:

$$Y_1 = \beta_1 x_1 + \sigma_{\varepsilon_1 \mu} \lambda_1 + \varepsilon_1 \quad (4.5a)$$

$$Y_0 = \beta_0 x_0 + \sigma_{\varepsilon_2 \mu} \lambda_0 + \varepsilon_0 \quad (4.5b)$$

The estimated coefficients of IMRs yield estimates of the correlation coefficients between error term of the selection equation and welfare outcome equations for RNFE participants and non-participants.

Computing treatment effects

The particular interest of the current study is to quantify the effects of RNFE participation on household welfare, in terms of consumption. Measuring impact as the difference in mean welfare outcomes between all RNFE participant and non-participant households, may give a biased estimate of the treatment. This bias would arise if there are unobserved characteristics that affect the probability of participation in RNFE and are also correlated with consumption. A suitable measure of the impact of RNFE participation should compare welfare outcomes in households that participate in RNFE to what those outcomes would have been had the same households not participated in RNFE. But this is not straightforward because only one of the potential outcomes is observed for each household and the counterfactual outcome is unobserved.

To deal with this, most evaluation studies construct an estimate of the *average treatment effect on the treated (ATT)*. Similarly, our focus lies on constructing an estimate of the average impact of the treatment (RNFE participation) on participant households. To do this, we need to compare the actual conditional expected consumption of a farm household that participates in non-farm activities with the counterfactual (that is, what could have been the welfare outcome (consumption) of participant households had they not participated).

Using Equations (4.2a) and (4.2b) from the endogenous switching regression model, the actual and counterfactual scenarios can be illustrated as follows:

$$\text{Actual scenario (observed): } E(Y_1|RNFE = 1) = \beta_1 x_1 + \sigma_{\varepsilon_1\mu} \lambda_1 \quad (4.6a)$$

$$\text{Counterfactual Scenario: } E(Y_0|RNFE = 1) = \beta_0 x_0 + \sigma_{\varepsilon_0\mu} \lambda_1 \quad (4.6b)$$

Equation (4.6a) refers to conditional expected value of consumption by a farm household that participates in non-farm activities while Equation (4.6b) refers to conditional expected value of consumption the same farm household would enjoy without participation.

$\sigma_{\varepsilon_1\mu}$ accounts for sample selection arising from the fact that a farm household participating in non-farm activities differs from other households with characteristics x and z because of unobserved characteristics.

Following Di Falco *et al.* (2011), we compute the **ATT** as the difference between expected outcome for households that participated in non-farm activities and the counterfactual hypothetical cases that they did not participate. The ATT can be presented as follows:

$$E(Y_1|RNFE = 1) - E(Y_0|RNFE = 1) = (\beta_1 - \beta_0)x + (\sigma_{\varepsilon_1\mu} - \sigma_{\varepsilon_0\mu})\lambda_1 \quad (4.7)$$

This parameter focuses directly on actual treatment effect on participants, thus, it can be used to measure the realized consumption gain from rural non-farm (RNFE) participation. ATT results from the differences in the coefficients and it accounts for all factors potentially leading to consumption differences.

If a farm household self-selects to participate in non-farm activities based on the comparative advantage, $(\sigma_{\varepsilon_1\mu} - \sigma_{\varepsilon_0\mu})$ would be negative, and participation in non-farm activities would produce bigger benefits in terms of consumption under self-selection than under random assignment (Maddala, 1983).

Equation (4.7) accounts for a possible upward bias of the treatment effect that we may get with a simple comparison of mean consumption in participant group $E(Y_1|RNFE = 1)$ and that in non-participant group $E(Y_0|RNFE = 0)$.

Similarly, we can compare the actual conditional expected consumption of a non-participant household with the counterfactual case that the same household would enjoy with non-arm participation, illustrated below.

$$\text{Actual scenario (observed):} \quad E(Y_0|RNFE = 0) = \beta_0 x_0 + \sigma_{\varepsilon_0\mu} \lambda_0 \quad (4.8a)$$

$$\text{Counterfactual Scenario:} \quad E(Y_1|RNFE = 0) = \beta_1 x_1 + \sigma_{\varepsilon_1\mu} \lambda_0 \quad (4.8b)$$

where $\sigma_{\varepsilon_0\mu}$ accounts for sample selection arising from the fact that a non-participant household differs from other households with characteristics x and z because of unobserved characteristics.

Average Treatment Effect on the Untreated (ATU) is computed as a difference between expected outcome values with and without treatment for non-participant households.

$$E(Y_1|RNFE = 0) - E(Y_0|RNFE = 0) = (\beta_1 - \beta_0)x + (\sigma_{\varepsilon_1\mu} - \sigma_{\varepsilon_0\mu})\lambda_0 \quad (4.9)$$

Farm households that participate in non-farm activities may have better welfare outcomes than non-participant households regardless of the fact that they decided to participate in non-farm activities, but because of unobservable characteristics such as entrepreneurial skill, knowledge, motivation and wealth. This is known as the **effect of base heterogeneity** (Di Falco *et al.*, 2011). Computation of the effect of base heterogeneity for participant and non-participant households based on conditional expectation equations is given by BH_1 and BH_0 respectively (see last row of Table 4.1).

Table 4.1: Conditional expectations, treatment, and heterogeneous effect

Sub-samples	Decision stage		Treatment effects
	To participate	Not to participate	
Participant households	(4.6a) $E(Y_1 RNFE = 1)$	(4.6b) $E(Y_0 RNFE = 1)$	TT= (4.6a) - (4.6b)
Non-participant households	(4.8b) $E(Y_1 RNFE = 0)$	(4.8a) $E(Y_0 RNFE = 0)$	TU=(4.8b) - (4.8a)
Base heterogeneous effects	$BH_1 = (4.6a) - (4.8b)$	$BH_0 = (4.6b) - (4.8a)$	(4.6a) - (4.8a)

Notes: (4.6a) and (4.8a) are the observed household welfare outcomes; (4.6b) and (4.8b) are the counterfactual expected welfare outcomes. TT is the effect of the treatment (RNFE participation) on the treated (participant households); TU is the effect of the treatment on the untreated (non-participant households); BH_1 and BH_0 refer to the effect of base heterogeneity for participant and non-participant households respectively.

4.4. Data and variables

The current study uses the first three waves of data from the Ethiopian Socio-economic Survey (ESS) (2011/12, 2013/14 and 2015/16) conducted by the Ethiopian Central Statistics Agency in collaboration with the World Bank. The focus of this study is on rural farmers in Ethiopia; thus, urban areas and small towns are excluded from the observations. We are able to construct a balanced panel data of 5,169 households (1,723 households observed in three waves) after cleaning, merging, and appending the data.

The main concern of this study is to analyze the impact of RNFE participation on welfare of rural farm households. Thus, the dependent variable in the outcome equation is household-level indicator of welfare, *aggregate household consumption expenditure*¹⁴, which consists of expenditures on purchased foods and the value of self-produced food, non-food consumption and education expenses (CSA, 2017). Consumption expenditure is reasonably a better measure of household well-being as it is need based and can be measured with more accuracy than income (Scharf and Rahut, 2014). Income is likely to suffer from measurement error. Income is widely under-reported for many different reasons, especially in case of economic opportunities outside of agriculture that are mainly in casual jobs in the informal sector where standard measures of output are unable to completely capture (Deaton, 2002).

The key explanatory variable of interest is related to *the decision to engage in non-farm employment or not*. It is a dummy variable that takes the value of “1” for RNFE participant households and “0” for non-participants. A farm household is considered to be RNFE participant if at least one household member was involved in non-farm business activities, over the past 12 months.

¹⁴ We use aggregate consumption as a measure of household welfare since the ESR model we use allows us to compare households with themselves. If we were to compare welfare across households, per capita consumption would have been a better measure to use.

Other independent variables used in this study include household characteristics that are peculiar to the household head, household demographic indicators, community characteristics and other socio-economic variables. These variables and their hypothesized effects are summarized in Table A-2 (Annex A) and discussed herein below.

Gender of the household head is coded as a dummy variable with a value one for male headed households and zero otherwise. There is considerable gender discrimination in traditional societies. Most of the female headed households are vulnerable to various shocks and stresses due to limited access to non-farm employment opportunities and productive resources such as land and education (due to discriminatory access as children) (Onya, Amah-Jerry, and Iheke, 2020).

Age and age squared of the household head are included to capture the life-cycle effects. Older household heads with accumulated experiences in rural way of life are more likely to diversify into non-farm activities and have higher welfare (Nagler and Naudé, 2017).

Education is measured in terms of ***years of education of the household head***, and it is hypothesized to stimulate RNFE participation (Barrett *et al.*, 2001; Lanjouw and Shariff, 2004). Well-educated household heads are equipped with work-related skills; hence they would have more job opportunities. Moreover, they would have easier access to information and be able to build better networks in the community.

Household size is another significant factor influencing RNFE participation decision. It is measured by the ***number of adult household members*** (men and women of prime working-age (15-65 years old), and ***dependency ratio*** (the share of inactive labor force within the household (less than 15 years and over 65 years) to economically active labor force (between 15 and 65 years)). It is difficult to hypothesize about the effects of household size due to the potentially mixed effects. On the one hand, large family size and household labor may imply a decline in the marginal value of leisure and an increase in the odds to participate in different income generating activities due to the need for high household income to satisfy food consumption and other necessary expenditures (Damenaa and Habte, 2017). On the other hand, large farm households with more dependents need to

spend more time taking care of these dependents, reducing the time available for non-farm activities.

We also control for the size of land owned by the household (in hectares) by categorizing landholdings into three: smallholders (with farms size of 0.50 hectare and less); medium size (0.51 - 2.0 hectares), and large size (above 2.0 hectares). Land endowment¹⁵ is less likely to be endogenous since land markets in rural Ethiopia are inactive.

Landholding is expected to influence household consumption positively; however, it is difficult to hypothesize about the effects on RNFE participation due to the potentially mixed effects. Rural households may be pushed to diversify into RNFE due to declining land size under population pressure (Bezu and Holden, 2014; Schmidt and Bekele, 2016; Van den Berg and Kumbi, 2006). On the other hand, households with large farm size are likely to be discouraged from engaging in RNFE as they can generate sufficient income from farming. On the other hand, such households can engage in more lucrative non-farm income generating activities by investing the likely high income generated from agricultural activities (Asfaw *et al.*, 2017; Prowse, 2015; Woldenhanna and Oskam, 2001).

Livestock holding is included as indicator for wealth status of households. Having larger stocks of animals is considered to positively influence household welfare through different channels: reducing risk aversion of households and relieving liquidity constraints (Damenaa and Habte, 2017). In rural Ethiopia, livestock serves both as a source of liquid assets as well as a productive resource in the form of draft power. As a capacity factor, livestock provides households with the income required to invest in non-farm activities. On the other hand, households with large livestock holding need to put in more farm working hours in managing their herd, and are able to generate income through sale of its

¹⁵ Total land area is employed instead of cultivated land area because the latter has a higher potential for endogeneity.

products and services; from this perspective they may have both less time and incentive to engage in RNFE.

Access to credit also matters since it affects both the decision to participate in different rural activities as well as household consumption. Access to credit in the form of cash is seen as a means of easing liquidity constraints for the households and allows them to spend more on food consumption, invest in health and education, or in non-farm enterprises; thereby enhancing household welfare. Thus, we control for credit access with a dummy variable taking the value one, if the household has access to credit and zero otherwise.

Smallholder farmers in rural Ethiopia are prone to various types of shocks such as drought, flooding, pests, and diseases which negatively affect welfare of households. Thus, we control for *community level shocks* such as occurrence of drought, flooding, too early availability of rain at the beginning of summer, lack of enough rainfall at growing season of crops, too early or too late stop of rainfall. Experience of such adverse shocks is hypothesized to affect farm households' decision regarding participation in farm and non-farm activities as well as household welfare (Lanjouw and Lanjouw, 2001).

Having better access to other well-developed infrastructures, in terms of proximity to market areas and all-weather roads, is considered as an incentive for rural population to engage in non-farm economic activities (Asfaw *et al.*, 2017). Thus, we controlled the household's *distance to the nearest large weekly market*. Farmers who live further away from the market centers are less likely to be involved beyond agricultural activities as it will be costly for farmers to engage in non-farm activities. The further away a farm household is from market area, the less opportunities for labor market and more commuting cost (Damenaa and Habte, 2017).

We include *dummy for regions* (Tigray, Amhara, Oromia and SNNP) in Ethiopia to control for the diverse agro-ecology and climate conditions, as well as time varying differences in local market conditions, employment opportunities, and land productivity. This helps to capture the diverse effects of socio-economic conditions on RNFE participation and welfare of farm households.

4.5. Empirical analysis and results

This section starts with descriptive analysis of the main variables of interest. Further analysis is run on the differences between rural farm households who participate in non-farm work and those who do not, to check whether they differ significantly in terms of household characteristics, farm characteristics and assets. The section ends by presenting the econometric analysis results.

4.5.1. Descriptive statistics of key variables

Summary of statistics of the variables supposed to have an impact on the decision of rural farm household to pursue non-farm economic activities and on household welfare (measured by consumption expenditure) are portrayed in Table A-3 (see Annex).

As shown in Table A-3, slightly more than 80 percent of households in our sample are male headed. This is to be expected in many poor countries like Ethiopia, where traditional male-dominated society prevails. It is not very common to see households headed by women. Mostly, men are bread winners of the household and the main decision makers in a rural society. According to the data, the average age of household heads is around 46 years, which indicates that the majority are in their productive age level. Almost half of the household composition is made up of dependents that are either below the age of 15 or above the age of 65 years.

The data demonstrates that, on average, approximately 24 percent of farm households diversify into non-farm self-employment or wage/salary employment. Most households in rural Ethiopia operate mainly small businesses (such as weaving, sewing or textile production, petty trading, trade in grains, fruit and vegetable vending, making and selling of food and local liquor drinks, handicrafts) and services such as traditional healer, religious teacher, plaiting of hair/barber. This is consistent with the findings of prior studies that show that rural households primarily engage in non-agricultural businesses or services from home, selling of processed agricultural products including food and local beverages and trading businesses such as selling goods on a street or in a market (CSA, 2017; Nagler and Naudé, 2017; Prowse, 2015).

Table 4.2 below shows results of independent samples t-test that is computed to compare the mean differences between households engaged in non-farm activities and those without such activities. There are some remarkable differences between RNFE participants and non-participants, as confirmed by simple statistical tests of differences in means.

Average consumption of rural non-farm work participant households is significantly higher than that of non-participant households¹⁶. However, there is no significant difference the average consumption per adult equivalent between the two groups of households.

Table 4.2: Characteristics of RNFE participant and non-participant farm households

Variables	Participants (n=1,381)		Non-participants (n=3,788)		Difference in means
	Mean	Std. Dev.	Mean	Std. Dev.	
Household consumption per annum	22244.4	17081.47	20401.79	16026.91	1842.61***
Household consumption per adult equivalent	5063.75	96.332	5056.25	64.772	7.50
Household head's gender (male)	0.84	0.366	0.81	0.392	0.04**
Household head's age	44.58	13.326	46.98	14.997	-2.40***
Household head's education	2.02	2.964	1.45	2.744	0.57***
Labor endowment	2.88	1.331	2.71	1.368	0.17***
Dependency ratio	0.53	0.188	0.52	0.214	0.01
Land size (ha)	0.40	1.063	0.50	1.130	-0.10***
Livestock holding (TLU)	0.72	1.658	1.20	2.598	-0.48***
Access to credit	0.40	0.489	0.33	0.471	0.06***
Covariate shocks	0.17	0.377	0.22	0.417	-0.05***
Distance to markets (KMs)	66.96	47.056	62.41	45.451	4.54***

**Test statistic significance at 5% level.

***Test statistic significance at 1% level.

¹⁶ The high standard deviation around the mean is indicative of high variability in magnitude of expenditure among households.

Average age of household heads is slightly lower for non-farm participants relative to non-participant households. From a gender perspective, a higher proportion of non-farm work participant households are male headed (84 percent). Perhaps this is related with the ease at which male heads can access assets that enable them to engage in non-farm enterprises.

Among non-farm work participants, household heads completed, on average, a two-year formal education while non-participant household heads completed less than two-year formal education. The difference in average years of schooling completed by household heads suggests that households headed by a better-educated person are more likely to engage in non-farm activities.

Non-farm work participant households own relatively smaller farm sizes as compared to non-participant households. On average, non-farm work participant households own 0.4 hectare of land, which is less than the average holdings for non-participant households (0.5 hectare of land). Similarly, RNFE participant households own less livestock than non-participants, suggesting these are alternate sources of livelihood for households. While the non-farm work participants own about 0.72 cow equivalents, the non-participants own 1.2 cow equivalents on average.

There is also a significant difference in relation to access to credit. Approximately 40 percent of non-farm work participants and 33 percent of non-participant households have access to credit.

Rural non-farm work participant households are less exposed to shocks relative to non-participant households. Only 17 percent of the non-farm work participant households faced covariate shocks in the given year while about 22 percent of non-participants reported to have faced similar shocks.

4.5.2. Econometric analysis

The descriptive analysis reveals significant differences in household consumption between RNFE participant and non-participant households. However, to properly evaluate the effects of RNFE participation on farm households' consumption, an endogenous switching regression model is estimated in two stages using valid exclusion variables.

A key challenge in analyzing the impact of RNFE on household welfare involves the selection of identifying variables that affect wellbeing solely through their impact on RNFE. In this study, we use two instruments as identification restriction based on economic theory and findings of past empirical studies.

One potential instrument is ***“Percentage of households participating in non-farm activities in the village”***. It reflects the availability of non-farm jobs and peer effects (as suggested by Scharf and Rahut, 2014). In most villages, households' behaviors and activities are heavily influenced by their neighbors; rural households adopt livelihood strategies and technologies based on what their neighbors are doing. This variable is also intended to capture the strength of clustering of non-farm activities at the village level and access to infrastructure necessary for participation in the non-farm sector (Lanjouw and Lanjouw, 2001). The notion here is that the variable influences probability of employment in the non-farm sector, but that conditional on employment it is not clear why this factor should influence consumption expenditure.

Another potential instrument is ***“Household's distance (in KMs) to the nearest population center with over 20,000 population”***. This instrument reflects household's remoteness and is expected to influence RNFE through its implication on transaction costs. Households residing far from population centers have less probability to access and participate in different income generating activities. However, it does not have any direct impact on household welfare indicators, and only affects household welfare indirectly through employment diversification.

Testing validity of selected instruments

Validity of instruments rests on two conditions: relevance and exogeneity. For the former to be fulfilled, variation in the endogenous variable (RNFE participation) must be explained by the instruments. For the latter, the chosen instrument must be orthogonal to the welfare outcome variable of interest. The first instrument (*Percentage of households participating in non-farm activities in the village*) is exogenous as it is unlikely for household welfare to influence village-level share of households participating in non-farm activities, although the second instrument (*Household's distance to population center*) may not be truly exogenous. It could be argued that households that are more likely to participate in non-farm activities are also more likely to move closer to population centers. However, our data show that mobility of rural households in Ethiopia is quite limited. Vast majority of surveyed households have been living in the same village for generations. Once we have already provided a theoretical explanation for exogeneity of instruments, we focus on relevance of instruments henceforth.

Following Di Falco *et al.* (2011), a simple falsification test is conducted to test validity of the selection instruments. Table A-4 (Annex A) presents estimates for the chosen instruments. Both instruments are statistically significant drivers of the decision to engage in non-farm activities but not of consumption for non-participant households.

It is also important to explain that the chosen instruments affect the welfare outcome only through the endogenous variable. To ensure that no other variable explains the impact of instruments on household consumption other than RNFE, we include a rich set of controls at the household-level to check if the results are not driven by the exclusion of some variables. And even after controlling for many characteristics, we find that our results remain unchanged: the effect of RNFE on household consumption remains significant. Thus, both *percentage of households participating in non-farm activities in the village* and *distance to population center* can be considered as valid identification instruments.

Correlated random effects (CRE) estimation

Estimation of the two-stage ESR is done based on correlated random effects framework using *Mundlak–Chamberlain* device with household-level time averages as additional controls. In the first stage of the two-stage ESR model, a probit model is estimated for households' decision to participate in non-farm activities. The first column of Table 4.3 presents average partial effects (APEs), which are parameters of interest in binary response panel data models. The second and last columns of Table 4.3 present estimates from the second stage of the two-stage ESR model with the respective regimes for consumption of non-farm participant and non-participant households. Coefficients are reported with robust standard errors (SE) in brackets.

According to the results from the selection and outcome models, household welfare and the likelihood of participating in non-farm activities are significantly influenced by age and gender of the household head, household size, land and livestock holdings, access to credit and distance to markets.

Gender of the household head is significant only for the outcome model. There is no significant difference in RNFE participation between male and female headed households once other characteristics of households have been taken into account. Yet, male headed households have higher consumption as compared to female headed households for both RNFE participant and non-participant households in rural Ethiopia.

The dependent variables for both the selection and outcome models have an inverted U-shape relation with age of the household head, implying that RNFE participation and household consumption increase with age for younger household heads and decrease after a certain age. This could be because most farm works are physically demanding hence adult children take over such farming activities while older farmers that have more experience in the rural way of life diversify into non-farm activities.

Table 4.3: Results from two-stage endogenous switching regression (ESR) model estimation

	Selection model	Outcome model	
	(RNFE participation)	Participants (n=1,381)	Non-participants (n=3,788)
head's gender (=1 if male)	0.001 (0.02)	0.120*** (0.02)	0.118*** (0.02)
head's age	0.015*** (0.01)	0.024*** (0.01)	0.050*** (0.01)
head's age squared	-0.000*** (0.00)	-0.000* (0.00)	-0.000*** (0.00)
head's education	-0.001 (0.00)	0.009 (0.01)	0.008 (0.01)
Labor endowment	0.024*** (0.01)	0.020*** (0.02)	0.162*** (0.02)
Dependency ratio	0.132** (0.05)	0.328*** (0.12)	0.553*** (0.10)
Land size (relative to <0.5ha)			
Smallholder(0.5-1ha)	-0.030** (0.01)	0.077*** (0.03)	0.027 (0.02)
Medium(1-2ha)	-0.030* (0.02)	0.115*** (0.04)	0.062** (0.03)
Large(>2ha)	-0.029 (0.02)	0.078 (0.05)	0.027 (0.05)
Livestock_holding	-0.007*** (0.00)	0.006 (0.01)	-0.004 (0.00)
Access to credit	0.029*** (0.01)	-0.009 (0.02)	0.041** (0.02)
Covariate_shock	-0.014 (0.01)	-0.010 (0.02)	-0.032 (0.02)
Distance to market	0.043*** (0.01)	-0.110*** (0.01)	-0.062*** (0.01)
Distance to pop.center	-0.027** (0.01)		
Share of RNFE in village	0.121** (0.05)		
RNFE participation		0.089** (0.04)	0.093** (0.04)
imr_participant(λ_1)		-0.119*** (0.04)	
imr_participant(λ_0)			0.220*** (0.06)
Constant		9.505*** (0.21)	8.861*** (0.10)
<i>Log pseudolikelihood</i>	-1863.5589		
<i>Wald Chi2(27)</i>	128.22	3085.53	4055.69
<i>Prob > chi2</i>	0.000	0.000	0.000

- The data source is LSMS-ISA (2011/12, 2013/14 and 2015/16). The analysis is based on a balanced panel dataset consisting of the three waves for the rural sub-sample.
- The dependent variable of the outcome model is the natural logarithm of household consumption. This is done to meet the linearity assumption.
- Household level time averages of all time varying explanatory variables are included as additional controls (household level CRE controls). We also controlled for region effects.
- **Test statistic significance at 5% level; ***Test statistic significance at 1% level.

Household size, as measured by adult members and dependency ratio, has statistically significant positive effect on RNFE participation and on household consumption. With regard to labor endowment, households with many household members are more likely to involve in non-farm activities, which may indicate the existence of surplus labor that can easily be shifted from one activity to the other. The positive effect of household size also implies the need to engage in alternative rural activities in order to fulfill the household's consumption requirement (Damenaa and Habte, 2017).

The main indicators of wealth in rural Ethiopia (Land and livestock holdings) have statistically significant negative association with RNFE participation. RNFE participation is more prevalent among households with marginal land sizes (less than 0.5 hectare) and small herd size reflecting the fact that some households are pushed into RNFE by necessity to obtain minimum level of consumption required. However, RNFE participation decreases with an increase in land size and livestock holdings since it is an alternative source of livelihood for rural households. Wealthier households are discouraged from participation in RNFE as they can satisfy the needs of their family from farm production. This result is consistent with the findings of prior studies from Ethiopia that document an inverted-u relationship between landholding and non-farm work participation (Asfaw *et al.*, 2017; Prowse, 2015; Woldenhanna and Oskam, 2001; Van den Berg and Kumbi 2006).

Furthermore, the statistically significant positive effect of land size on the outcome model of RNFE participant households suggests that larger farm size, in addition to economies of scale in production, is welfare enhancing probably because it enhances capacity of households to engage in lucrative non-farm activities.

Given the fact that rural farm households often face liquidity constraints, access to credit is identified to be one of the salient determinants of non-farm employment in the literature (Nagler and Naudé, 2017). In consonance with the literature, credit access is found to be associated with a higher likelihood of participating in non-farm activities in rural Ethiopia and improve welfare of households that do not participate in non-farm activities.

Farm households residing further away from markets are found to be more likely to participate in non-farm activities although they are worse off in terms of welfare. This could be because of gradual electrification, use of preservation of agricultural products, and infrastructural development that reduce the market distance induced gap.

As expected, we have significant coefficients for the exclusion variables. The negative coefficient for distance to population center reflects that households residing far from population centers are less likely to participate in non-farm activities, may be because they have limited access to information and infrastructure necessary for participation in the non-farm sector. The positive coefficient for percentage of households participating in non-farm activities in the village reflects peer effects, whereby rural households in such villages have better access to entrepreneurial skills and information concerning alternative income generating activities. It may also be the case that such villages have the infrastructure needed to operate non-farm businesses.

Effect of non-farm participation on household consumption

The significant coefficient of RNFE participation confirms anecdotal evidence about the role of non-farm employment in promoting welfare of farm households in rural areas. On average, RNFE participation causes about nine percent increase in household consumption per annum (see Table 4.3). Other studies from Ethiopia have also reported similar results. For instance, Bezu *et al.* (2012) have reported a positive effect of non-farm employment on consumption expenditure, with relatively wealthier households benefiting more from non-farm activity than poorer households.

Estimated coefficients of the predicted Inverse Mills Ratios (IMRs) are statistically significant for both RNFE participants and non-participants. These coefficients refer to covariate terms and imply non-zero correlation between error term of the selection equation and the welfare outcome equations for both participants and non-participants. This provides evidence of self-selection and endogeneity that needs to be controlled in the model specification of consumption equations.

Statistical significance of the covariance term of RNFE participants (coefficient of λ_1) indicates the presence of self-selection, where RNFE may not have the same effect on non-participants if they choose to participate. Similarly, the significant covariance estimate for non-participants suggests that in the absence of RNFE, there would be significant difference in average consumption of the two categories of farm households caused by unobservable factors.

The negative sign of the coefficient of λ_1 for households that participate in non-farm activities indicates a positive bias, suggesting that farmers with above-average consumption levels have higher probability of participating in RNFE. This finding is consistent with earlier studies by Seng (2015) and Anang (2017) but in contrasts with the findings of Dedehouanou *et al.* (2015) where they reported a negative bias for self-employment in Niger.

Overall, these results confirm that the Endogenous Switching Regression (ESR) model is an appropriate model for controlling self-selection and inherent differences between non-farm participants and non-participants. There is evidence of systematic differences across the two regimes. The estimated results demonstrate that household characteristics that influence RNFE also affect household consumption.

Treatment effects of non-farm participation on household consumption

The actual (observed) expected household consumption for RNFE participant and non-participant households are generated from Equations (4.6a) and (4.8a) and are approximately ETB 17,677 and ETB 16,276 respectively (see Table 4.4). Comparison of these two figures reveals that a base level difference between the two groups is ETB 1,401.42 (US\$ 49.05)¹⁷. That is, RNFE participant households have about ETB 1,401 more annual household consumption than non-participant households.

¹⁷ US\$1 = 28.57 Ethiopian Birr

This result compares very well with the descriptive statistics presented in Table 4.2. However, such simple and direct comparison of mean consumption between participant and non-participant households could be misleading and may result in an upward biased treatment effect. So, it is vital to take into consideration observed and unobserved characteristics of the two groups that could be correlated with their respective household welfare outcome (household consumption) (Lokshin and Sajaia, 2004).

To disentangle the effect of the treatment (RNFE participation) from observed and unobserved heterogeneities between participant and non-participant households, we build the counterfactual scenarios of expected values for the two groups of households from the Endogenous Switching Regression (ESR) estimates.

The difference in consumption conditional on participation is computed as in Eqn. (4.7), by comparing conditional expected consumption by RNFE participant households, $E(Y_1|RNFE = 1) \cong \text{ETB } 17,677$, to what they would have enjoyed if they did not participate in non-farm activities, $E(Y_0|RNFE = 1) \cong \text{ETB } 17,447$. Thus, the consumption gains that farm households on average make when participating in non-farm activities is $(E(Y_1|RNFE = 1) - E(Y_0|RNFE = 1)) = \text{ETB } 230$ (US\$ 8.05) per annum (see Table 4.4).

The treatment effect among the treated only explains about 16 percent of the base line consumption gap between participant and non-participant households (*i.e.*, $\frac{TT}{TH} = \frac{230.2}{1401.42}$). The remaining consumption gap is explained by base level heterogeneity. For instance, if RNFE participant and non-participant households had the same level of skills, participating households would consume ETB about 1,171 (7 percent) less than non-participants.

It is also possible to compute the counterfactual hypothetical effects for non-participants given the selection effect for non-participants. Non-participating farm households would lose, on average, ETB 140 (US\$ 4.90) per year in terms of consumption by participating in rural non-farm activities (see Table 4.4).

Table 4.4: Conditional expectations, treatment, and heterogeneous effect

Sub-samples	Decision stage		Treatment effects
	To participate	Not to participate	
Participant households (n=1,381)	$E(Y_1 RNFE = 1) = 17677.41$	$E(Y_0 RNFE = 1) = 17447.21$	TT = 230.20
Non-participant household (n=3,788)	$E(Y_1 RNFE = 0) = 16135.8$	$E(Y_0 RNFE = 0) = 16275.99$	TU = -140.19
Base heterogeneous effects	BH ₁ = 1541.61	BH ₀ = 1171.22	TH = 1401.42

Note: The data source is LSMS-ISA (2011/12, 2013/14 and 2015/16).

Overall, the results suggest that RNFE participation is effective in enhancing welfare of farm households in rural Ethiopia. This result is in line with those of Bezu et al. (2012) and Woldegabriel (2016), who showed that non-farm employment helps to increase rural household income and household consumption; thus, ensure improved welfare of households in Ethiopia. This supports the idea that rural non-farm employment has the potential to play a key role in the development of Ethiopia's rural areas by helping to induce better welfare of rural households through the provision of alternative source of employment and income.

4.6. Conclusion, policy implications and recommendations

The study evaluates the impact of rural non-farm employment (RNFE) participation on welfare of farm households in rural Ethiopia based on a balanced panel data from the first three waves of the Ethiopian Rural Socio-Economic Survey (ERSS).

Evaluation of true causal impact is carried out using an Endogenous Switching Regression (ESR) model in correlated random effects framework. The empirical method used is appropriate as it controls for all confounding factors resulting from selection bias and structural differences between the two groups of households: RNFE participant households are found to be systematically different from non-participant households the in terms of socioeconomic and demographic characteristics, as well as welfare indicators.

We find that age of the household head, household size, land and livestock holdings, access to credit, and distance to the nearest market are the most important factors influencing households' decision to engage in RNFE. Additionally, our results suggest that RNFE participation helps to increase household consumption, thus enhance welfare of farm households in rural Ethiopia. RNFE participant households make a positive, albeit small, consumption gain from participating in non-farm activities. On average, they gain ETB 230 (US\$ 8.05) worth of consumption per year when participating in non-farm activities. On the contrary, non-participating farm households would lose, ETB 140 (US\$ 4.90) per year on average in terms of consumption by participating in rural non-farm activities.

This study, therefore, concludes that participation in non-farm employment improves welfare of farm households who choose to engage in such employment; hence, it is rational for the RNFE participating household to participate in non-farm activities. Nevertheless, it is rational for the typical non-participating household not to participate in RNFE as there are no expected positive consumption gains from engaging in non-farm activities among the households who do not currently choose to do so.

The findings that emerge from this particular empirical study point to different policy implications and recommendations to improve rural livelihoods in Ethiopia.

First and foremost, considerable attention should be given to non-farm activities as an important potentially welfare enhancing livelihood strategy, particularly as farming alone may fail to guarantee a sufficient livelihood for most farming households. Yet, not all types of non-farm employment are expected to be welfare improving. The small magnitude of the consumption gains reported in this study for RNFE participating households, and the potential loss for non-participants may suggest that the existing rural non-farm activities are not very helpful probably because such activities involve operating low-return non-farm business that are resource-constrained and small scale in nature. As such, efforts are required to turn them into viable sources of livelihoods. Governments and development agencies should make concerted efforts to address the major constraints faced by rural non-farm businesses and provide the necessary support for such businesses to thrive.

Second, the factors which are identified to significantly influence RNFE participation and household consumption should be taken into account when strategizing how to improve rural livelihood in Ethiopia. In this regard, serious attention should be given to policy measures that improve infrastructure and thereby reduce transportation and transaction costs to increase overall employment opportunities; as well as policies that enhance the capacity of households (particularly poor households) to participate in non-farm activities. Entry barriers to non-farm activities should be removed to facilitate RNFE participation of the disadvantaged such as the land-poor and credit constrained households in rural Ethiopia. For instance, improving access to credit helps to ease liquidity constraints and allows rural households to engage in lucrative and welfare enhancing non-farm activities. This is supported by our finding of a significant positive effect of credit access on welfare of RNFE non-participant households as well as results from other studies suggesting that expanding access to credit is likely to bring about improvements in rural livelihoods in many developing countries.

The current study has some limitations. First, this study does not distinguish between different types of non-farm activities in rural areas since the data used for this study does not have detailed information on the nature of non-farm activities in rural Ethiopia. Yet, it is acknowledged that rural non-farm activities are heterogeneous and have different effects on welfare of participating households. For instance, participation in high-return non-farm activities can allow rural farm households to increase their consumption and, thus, improve their household welfare. However, this may not be the case for low-yield and sometimes risky non-farm activities that most poor rural households are forced to engage in for survival. Second, the analysis in this study is limited to examining the impact of non-farm employment participation, with no regard to the extent of participation.

Further research should be carried out by taking these limitations into account. Future studies may find it helpful to extend the analysis based on high-quality data which will allow a more rigorous contextual analysis, accounting for the diversity in the non-farm sector and looking further into hours allocated to non-farm activities or the amount of income earned from such activities.

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APPENDICES

Table A-1. Summary definition of variables

Variables	Definition
<i>Dependent Variables</i>	
Household consumption	Natural logarithm of household consumption expenditure per annum, measured in Ethiopian Birr (ETB).
Rural Non-Farm Participation	A binary variable that is equal to “1” if a household member participated in any non-farm business in the last 12 months; “0” otherwise.
<i>Explanatory Variables</i>	
Household head’s gender	A binary variable that is equal to “1” for male headed households, “0” for female headed households.
Household head’s age	Household head’s age in years.
Household head’s education	Household head’s years of formal schooling.
Labor endowment	Number of adult members of household (15-65 years).
Dependency ratio	Share of inactive members (under the age of 15 or over the age of 64) to labor force (between 15 and 65 years).
Land size (ha)	Land area owned by farm household in hectares.
Livestock holding	Livestock measured in Tropical Livestock Unit (TLU), equals 1 for camel, cattle 0.7, sheep and goats 0.1, horses/donkey/mules 0.5, and chickens 0.01.
Access to credit	A binary variable that is equal to “1” if any household member has taken out credit over the past 12 months, “0” otherwise.
Covariate shocks	A binary variable that is equal to “1” if farm household suffered shocks (such as excessive rainfall and/or flood, drought) over the past 12 months, “0” otherwise.
Distance market	Distance to the nearest market in kilometers.
Distance to population center	Distance to population center with >20000 people
RNFE share in the village	Proportion of households that own non-farm enterprise in the village

Table A-2. Variables with their hypothesized effects

	Expected sign	
	Selection model (RNF Participation)	Outcome model (Household consumption)
<i>Dependent variables:</i>		
Household consumption	Na	√
RNF Participation	√	na
<i>Explanatory variables:</i>		
Household head sex (=1 if male headed)	+	+
Household head age (years)	+	-
Household head education	+	+
Labor endowment		
Dependency ratio	+/-	+/-
Land size (ha)	+ /-	+
Livestock holding	+/-	+
Access to credit	+	+
Covariate shocks	+	+
Distance to market	-	-
<i>Identification instruments</i>		
Distance to population center	-	na
RNFE share in the village	+	Na

Table A-3. Summary statistics of variables used in regression.

Variables	Obs.	Mean	Std. Dev.	Min	Max
RNF participation	5,169	0.24	0.428	0	1
Household consumption	5,169	20615.23	15945.670	780	183621
Household head's gender	5,169	0.83	0.376	0	1
Household head's age	5,169	46.55	14.852	18	98
Household head's education level	5,169	1.74	2.831	1	15
Labor endowment	5,169	2.76	1.350	0	10
Dependency ratio	5,169	0.52	0.202	0	1
Land size (ha)	5,169	0.53	1.252	0	19.722
Livestock holding	5,169	0.97	2.038	0	68.6
Access to credit	5,169	0.37	0.483	0	1
Covariate shocks	5,169	0.20	0.397	0	1
Distance to market	5,169	62.06	43.816	0.5	256
Distance to population center	5,169	35.31	25.617	1	208.2
RNFE share in the village	5,169	0.15	0.104	0	0.5

Note:

- *All the reported statistics are weight-adjusted for the complex survey design.*¹⁸
- *The data source is LSMS-ISA (2011/12, 2013/14 and 2015/16).*

¹⁸ The weighted sample has 10 strata with 3, 4, 5, 6, 7, 9 or 10 PSUs in each. There are 56 Primary Sampling Units (PSUs), where there are different number of observations in each PSU and in each strata. There are 5,169 observations in the PSUs with a minimum of 3, a maximum of 552 and an average of 93 observations in the PSUs.

Table A-4. Parameter estimates – test for validity of the selected instruments

	RNF Participation		Consumption for non-participants	
	Coef.	SE	APE	SE
H head's gender	0.010	0.02	0.162***	0.04
H head's age	0.015***	0.01	0.044***	0.01
H head's age squared	-0.000***	0.00	-0.000***	0.00
H head's education	-0.001	0.00	0.013	0.01
Labor endowment	0.024*	0.01	0.144***	0.01
Dependency ratio	0.132***	0.05	0.491***	0.11
Land size (relative to <0.5 ha)				
Smallholder(0.5-1.0ha)	-0.030**	0.01	0.052**	0.02
Medium(1.0-2.0ha)	-0.030*	0.02	0.104***	0.03
Large(>0.2ha)	-0.029	0.02	0.086**	0.05
Livestock_holding	-0.007***	0.00	-0.003	0.00
Access to credit	0.029***	0.01	0.030	0.02
Covariate_shock	-0.014	0.01	-0.045*	0.03
Distance to market	0.043***	0.01	-0.038*	0.02
Instruments				
Distance to pop.center	-0.027**	0.01	-0.037	0.03
Share of RNFE in village	0.121**	0.05	0.102	0.09
Constant			8.878***	0.16
Observations	5,169		3,788	
Log pseudolikelihood	-1863.5589			
Wald Chi2(27)	128.22		1068.84	
Prob > chi2	0.000		0.000	

Note:

- The data source is LSMS-ISA (2011/12, 2013/14 and 2015/16). The analysis is based on a balanced panel dataset consisting of the three waves for the rural sub-sample.
- *Test statistic significance at 10% level. **Test statistic significance at 5% level.

CHAPTER FIVE

CONCLUSION AND POLICY IMPLICATIONS

The purpose of this dissertation is to shed light on key issues that characterize labor markets in rural areas. It makes the case for the Ethiopia rural labor market in three interlinked papers. The papers relate to overall research questions and objectives specified in the introductory chapter of this dissertation. The papers entail insights that help to better understand the functioning of rural labor market in the study context.

The first paper investigates the major factors which undoubtedly play important roles in determining the way adult male and female members of farm households allocate their time across rural activities. The determinants are evaluated both at the extensive and intensive margins using a Two-Parts Model (TPM).

The second paper tests whether exposure to idiosyncratic and covariate shocks induces an increase in child labor. The analysis is done using multilevel mixed effects tobit model considering the hierarchical structure of data where children are nested within households. The study exploits the dynamics in child work and educational attainment over time, conditional over other relevant covariates.

Finally, the third paper looks into farm households' decision to diversify into rural non-farm employment (RNFE) and evaluates effects of such endeavor on welfare, by quantifying the likely gains or losses in consumption resulting from RNFE participation. An Endogenous Switching Regression (ESR) approach is used to evaluate the true causal impact of RNFE on welfare of farm households in rural Ethiopia, accounting for potential selectivity and endogeneity biases.

This chapter presents a summary of key findings, discusses conclusions in relation to the limitations of the research, based on the findings forwards policy recommendations and sets out some potential avenues for future research.

5.1. Summary of key findings

Overall, the dissertation has the following significant findings with contribution to the literature on the shocks induced intra-households reallocation of non-farm work participation and their effects on gender disparity in labor allocation, child work and its intensity, educational attainments, and welfare of rural population in developing countries.

Paper 1 provides empirical evidence for women's and men's participation in non-farm employment in rural Ethiopia. The main finding reveals that women (unless with many infants) are more likely to participate in non-agricultural works, and when they do, they also work more hours than males. In rural Ethiopia, labor allocation to non-farm activities is driven by both incentive (pull/push factors) and capacity factors, with individual attributes and household characteristics as most important drivers of participation in non-farm employment. The research hints that women, youth, and the land-poor households engage more in non-farm activities. More importantly, the study reveals that there is gender disparity in labor allocations in rural Ethiopia. There is marked difference in response to factors, such as education and non-labor income, which affect the labor allocation decisions of men and women. Differences between men and women also relate to household composition, with a positive effect of child dependency ratio on women's participation in non-farm employment in rural areas.

Paper 2 confirms the claim that shocks induce child work, and child labor (excessive hour of child work) adversely affects educational attainment of children in rural Ethiopia. Furthermore, the study provides empirical evidence on the heterogeneous effect of shocks on child labor in rural Ethiopia. Exposure to idiosyncratic shocks is found to significantly increase hours of child work in economic activities while covariate shocks increase total hours of child work, including time spent fetching water and firewood. There is gender bias in child labor when households face shocks; only girls seem to experience harmful effects from both idiosyncratic and covariate shocks, in terms of increased hours of work. The findings further show that non-labor income and credit access serve as buffers against idiosyncratic and covariate shocks and ease the effects on child labor for certain children in rural Ethiopia.

Paper 3 provides empirical evidence on the major factors that drive RNFE participation in rural Ethiopia. Age of the household head, household size, land and livestock holdings, access to credit, and distance to the nearest market are the most important factors influencing households' decision to engage in RNFE. Furthermore, the study provides evidence that supports the hypothesis that rural non-farm employment (RNFE) is welfare enhancing. RNFE participant households make a positive, albeit small, consumption gain (ETB 230 (US\$ 8.05) worth of consumption per year) from participating in non-farm activities, even after controlling for all confounding factors. On the contrary, non-participating households would lose ETB 140 (US\$ 4.90) worth of consumption per year on average by participating in rural non-farm activities, given their characteristics and circumstances.

5.2. Limitations of the research

Besides contributions and success achieved, this dissertation has certain limitations. This section discusses some of the limitations and points at some caveats which should be borne in mind when considering the results discussed above.

First, from the 'theoretical framework' perspective, measures of some variables in the analysis are not ideal. For instance, rural labor allocation decisions are indicated by variables that consider attributes of only the decision maker, without venturing into intra-household dynamics among the members.

Specifically, in paper 3, the main variable of interest (dummy for RNFE participation) is measured at household level considering household as an economic unit that works together for the common good of all members. RNFE participation is measured at household level because the available data does not allow us to distinguish which household member participated in non-farm employment and to what extent.

Besides, the measure does not indicate nature of the non-farm employment as the available information does not allow us to distinguish among different types of non-farm activities with adequate granularity. However, treating non-farm employment as a homogenous

group of jobs can lead to misleading inferences about issues like determinants of non-farm participation.

The limitation of the measure may cast some doubt on our results, and it may also affect the interpretation of the effect associated with RNFE participation. For instance, the lack of the expected high effects of RNFE may relate with nature of RNFE. It could be due to the prevalence of certain low return non-farm activities that are closely linked with the weather-sensitive agriculture production that may not improve welfare of farmers when hit by weather shocks. Accuracy of findings, conclusions and recommendations regarding involvement of rural employees in the RNFE can be improved by adding more explanatory factors regarding employer's and job's characteristics in rural areas.

Another limitation relates to the household welfare measure used in paper 3: annual consumption expenditure. Even though the study has important findings about the role of RNFE participation in rural Ethiopia, it leaves many questions about the role of RNFE participation in terms of increasing income and food security, reducing vulnerability, and improving households' resilience against different shocks.

A common shortcoming of the empirical studies included in this dissertation is that they do not account for potential heterogeneity characterizing the results. For instance, in paper 2, the effect of shocks on child labor may not be the same for households of different status. Likewise, in paper 3, the welfare impacts of RNFE may not be the same across households. For instance, while relatively better off households have access to a range of alternative instruments to cope with risks, RNFE is often the only viable alternative for the poorest households (with low consumption) that have limited risk management and coping capacities. Thus, RNFE may be more important for the poor.

Furthermore, due to paucity of detailed time use and earnings data, we failed to capture a number of essential factors that help to achieve further understanding of the functioning of rural labor markets. For instance, the ERSS data used does not provide comprehensive information on time use in household activities, such as time spent on domestic chores including cooking, cleaning and so on. Yet, rural girls and women spend long hours on

such activities, and this is likely to limit their time available to other works. This may lead to understatement of reported hours of work on rural economic activities.

There is also lack of data on important aspects, such as electricity connectivity and other energy sources, which significantly affect time use and employment conditions. For instance, connectivity to electricity will lead radical changes to the traditions of lighting, food processing, and cooking; the practice of farming and non-farming activities and the determinants of non-farm work participation; the use of advanced production technology and information technology (*eg.* allow use of media and internet connectivity). Also, it affects child labor, gender equity, knowledge, educational outcomes, poverty, and wellbeing of the rural areas. Yet, in this dissertation, we did not use data on electricity to control for the above mentioned potential effects.

Besides, we failed to use actual information on wages due to lack of records as most rural non-farm works are informal in nature and non-monetary payments for labor are common in rural areas. Instead of using wage or shadow wage, we attempted to control for the effect of wages by including information on exogenous variables that affect individual's shadow price of time and the reservation wage rate.

Last but not least, findings of studies included in this dissertation should be seen as exploratory rather than conclusive and definitive. These investigations are useful for better understanding of the topics referred rather than accepting or rejecting theoretical propositions. Besides, the analysis in paper 1 is done on pooled cross-sectional data, so estimated effects should be considered as associations as opposed to causal effects. Further econometric analysis is required to make inferences about the causal effects of individual and household characteristics. Another caveat is that some of the analysis in this dissertation suffers from potential endogeneity problem that may result from using subjective self-reported measures of shocks and welfare indicators.

5.3. Policy implications

The findings that emerge from the particular empirical studies which constitute this dissertation point to several policy implications.

First and foremost, the findings highlight the importance of non-farm activities in rural Ethiopia although agriculture remains by far the primary source of employment and income for the rural population. Therefore, considerable policy attention should be given to non-farm activities as an important livelihood strategy of farm households in rural Ethiopia, particularly as farming alone may fail to guarantee a sufficient livelihood for the growing population and majority of the rural land-poor households. Policy makers should pay more attention to non-farm activities when designing policies and programs that aim to improve efficiency in labor allocation and rural livelihoods.

To be precise, policy makers need to look into the determinants of involvements in rural non-farm activities; as well as the implications. In this way, the revealed findings are highly policy relevant. The results from paper 1 reveal that the involvements in rural non-farm activities are influenced (either negatively or positively) by individual attributes, household characteristics and local endowment. These factors should be considered when strategizing how to improve rural livelihood in Ethiopia. The results from paper 1 also hint that especially, vulnerable groups (such as women, youth, and the land poor) engage more in non-farm activities. Findings emerging from such empirical research are helpful to better understand the employment situation in specific settings, as to informing policy makers on ways to improve rural livelihoods.

Serious attention should be given to policies and interventions that enhance the capacity of households (particularly poor households) to participate in non-farm activities. This is because RNFE participation may enhance income-generating capacity of households and help mitigate the effects of transitory income shocks. Besides, paper 3 supports that non-farm work participation is important for rural households' welfare. Development policies should take note of this aspect. Ascertaining the welfare enhancing role of non-farm work participation is helpful to inform policy makers on ways to improve rural livelihoods in Ethiopia and other developing countries.

Overall, the reported results encourage policy approaches that target expansion of rural non-farm employment opportunities, encouraging non-farm participation and for improving non-farm incomes. Expansion of access to non-farm activities requires concerted efforts to provide the necessary environment and support for such activities to thrive. Equally important is to make sure that such activities are welfare enhancing. This requires looking into the nature of activities.

For instance, non-farm activities may not be welfare enhancing if they mostly involve operating non-farm business that are resource-constrained and small scale in nature. In such cases, efforts are required to turn them into viable sources of livelihoods by addressing the major constraints faced. The necessary support should be in place to facilitate successful RNFE participation of the identified vulnerable groups, such as the land-poor and credit constrained households in rural Ethiopia. Improving access to credit helps to ease liquidity constraints and it allows rural households to engage in lucrative and welfare enhancing non-farm activities.

Another key finding of this dissertation relates to the issue of child labor. Paper 2 shows the prevalence of child labor in rural Ethiopia and identifies important determinants of child labor. The findings are helpful to identify mechanisms that can be used to tackle the child labor problem and its negative effects on working children's educational attainment. The paper provides a thorough investigation of the heterogeneous effects of shocks on child labor. The significant effect of shocks on child labor points towards the need to design policies and interventions that would raise household income, enhance resilience, and empower households to withstand some shocks without resorting to child labor.

Besides, Paper 2 has identified buffering mechanisms (such as non-labor income and access to credit) which help to ease the pressure to rely on child labor when hit by shocks. A key policy relevance of these findings is that improved access to credit and non-labor income, along with formal insurance schemes (such as social safety nets and other social protection schemes) could play an important role in reducing the adverse effects of transitory shocks on household income and help prevent households from having to rely on child labor as a coping strategy in the face of shocks.

Furthermore, the finding of negative effect of child labor on educational achievement has important policy implications. The problem can be solved by formulating policies and interventions aimed at curbing child labor and its repercussions. Such interventions should be reinforced with efforts to enforce and incentivize schooling of children, say by providing households with incentives to keep children in school (such as payment of cash transfer conditional on children attending school).

An important finding of this dissertation with strong policy implication is that of heterogeneity. Empirical findings highlight the need to recognize heterogeneity in the effect of some factors that influence rural labor allocation decisions. Gender stands out as a key attribute with distinct implications on most of the reported results. Paper 1 reveals differences in response to the various factors that affect labor allocation decisions of male and female members of farm households. Also, paper 2 hints gender biases in the effect of shocks and some coping strategies. Such differences in responses should be considered in designing policies that aim at improving employment outcomes and eliminating child labor in rural areas.

As some interventions may have negative knock-on effects worsening gender inequality, it is imperative to assess factors which may reduce or exacerbate gender equality. And intervention programs need to be gender-sensitive in their design in order to have gender-equitable effects.

In a nutshell, findings of this dissertation plea for combination of properly designed policies that aim at improving the efficiency of rural labor markets, curbing the demand for child labor, increasing overall rural employment, encouraging successful livelihood diversification and enhancing income generating capacity of rural households.

The country would benefit from pursuing and intensifying its efforts to improve functioning of rural labor markets and accelerating rural development and transformation. Thus, there is a need for in-depth empirical studies that tell us specifically what has made a positive difference and what has not.

5.4. Avenues for future research

This concluding section briefly highlights several possibilities to further advance some of the research ideas developed in this thesis.

Rural employment and rural labor market development remain to be imperative for rural development and transformation in Ethiopia. Therefore, further studies in these fields should essentially be conducted for better and comprehensive understanding of the rural conditions and potential developments.

A possible future research direction is restating the research questions in this thesis taking intra-household dynamics into account. An attempt should be made to jointly model labor supply decisions of household members considering the possibility of interdependence of decisions. Further analysis of individuals' time allocation to various household and economic activities is merited in order to fully understand rural labor allocation and division of labor among farm household members. This will address a gap in the currently available empirical literature.

Another future research avenue is the need to analyze RNFE by classifying activities into groups such as low-return/high-return, full-time/part-time, and self-employment/wage-employment. Disaggregated analysis is likely to be more illuminating. In this regard, further analysis on dynamics of RNFE is merited in order to fully understand the nature of non-farm activities. This can be done by capturing employment status of individuals and households in each wave of the ERSS data and examining drivers of entry into, continue and exit RNFE. This helps to check whether non-farm activities in rural Ethiopia are characterized by stable or unstable jobs that hamper their contributions to household's welfare.

Having detailed information on nature of non-farm activities is important to account for the fact that motivations, means and outcomes of involvement in non-farm activities are heterogeneous. It helps to identify the reason for participation in non-farm activities either as a survival/coping strategy or distress driven. And this is useful in evaluating economic significance of non-farm activities; it helps to have thorough evidence about which

particular non-farm activities are beneficial. In this regard, it is also important to evaluate the impact of non-farm activities on different aspects of household welfare such as income, food security, vulnerability, and resilience.

Another possible research avenue is investigating heterogeneity of the reported results. For instance, the possible heterogeneous impacts of RNFE on welfare of households can be evaluated using a quantile treatment effect model which accounts for potential heterogeneity characterizing the impacts at different levels of the welfare distribution. This can help to identify policy options that are better tailored to the needs of a socio-economically diverse rural population.

More can be done exploring the rich ESS data and its panel nature, using appropriate econometric analysis that controls for potential time-invariant unobserved heterogeneity as well as potential endogeneity related to selection bias. Furthermore, it is possible to merge the ESS data with other datasets to deal with endogeneity issues. For instance, endogeneity arising from self-reported shocks in household surveys can be dealt with by integrating the household level ESS data with other datasets that have objective measures of shocks. It is possible to merge the household survey data with the geo-referenced weather data at the Enumeration Area (EA) level as spatial coordinates of households are known.

With the falling share of the agricultural sector and increasing share of the service sector, electrification of rural areas has become crucial for growth and achievement of the sustainable development goals. Particularly with growing population and scarce farmland, electrification will allow rapid expansion of services as the most important source of employment creation and income for the land-poor and unemployed household members. This accentuates the importance of connectivity to the grid and use of the information in future research in modelling of effects of shocks on intra-households' time allocation decisions.