The Effect of Migration on Child Labor in Rural Areas of Raya Kobo and Angot Districts, Ethiopia

Mengistu Abate Weldeyesus[1] and Bamlaku Alamirew Alemu[2]

Abstract

This study delves into the effects of migration on child labor within rural kebeles of Angot and Raya Kobo Districts, North Wello, Ethiopia. Data was collected from 431 households randomly chosen across four kebeles. Data analysis Both descriptive and inferential statistical techniques were used to analyze the data. The findings revealed that the working-age migration reciprocally impacted child labor in the migrant households in the study area. Moreover, the migration of working-age family members exposes children within migrant families to extensive hours of labor. The Propensity Score Matching (PSM) analysis underscores that children residing in households with migrant family members exhibited a higher likelihood of engagement in family labor and dedicated increased weekly hours to work compared to their counterparts in non-migrant families. Some of the factors that expose children of households with migrant families are poor financial rewards of education and the expansion of other business activities that drain the financial benefits of migration instead of child education. This study emphasizes the importance of supporting legal migration routes to save migrants from participating in illegal migration routes. It also suggests increasing public awareness of the detrimental impacts of child labor. It places a strong emphasis on enabling rural families to use their migration earnings to fund their kids' education and well-being. A comprehensive strategy for sustainable development in rural parts of the study areas is necessary to address the issue of migration-induced child labor.

[1] Centre for Rural Development, College of Development Studies, Addis Ababa University, Addis Ababa, Ethiopia
[2] Yom Postgraduate College, Addis Ababa, Ethiopia

Keywords: Child labor, migration, migration routes, working hours, children's wellbeing

1. Introduction

Child labor has become a worldwide concern, especially in underdeveloped countries (Kaur and Roger, 2021). Its prevalence, however, varies greatly throughout the globe. A greater percentage of all child laborers (90%) are found in Asia and Africa (ILO and UNICEF, 2021), While the number is the largest in Asia (Takeshimaand and Vos, 2022), the prevalence is highest in Africa (ILO and UNICEF, 2021). With 60 percent of children working in some capacity and 42.5% of the 7 to 14-year-old population in the country working in dangerous conditions, Ethiopia is one of the ten countries with the highest rates of child labor (Ghosal and Teferi 2018). Similarly, the 2018 surveys by the ILO and CSA found that 83.7 percent and 42.7 percent of Ethiopian children between the ages of 5 and 17 are, respectively, child laborers and child workers (ILO and CSA, 2018). The same source showed that the proportion of child labourers in rural areas was higher (42.7 percent) than that of urban areas (14.7 percent), and the highest percentage (54.9 percent) of child labor was in Amhara.

Since the beginning of the Industrial Revolution, different stakeholders have been paying more attention to child labor (Majeed and Kiran, 2019). Similarly, scholars studying child labour have been focusing on the determinants, eradication strategies, and indirect effects of trade liberalization on child labour with different recommendations for the uptake of policies and strategies (De Gaetano, et al.,2016). Following the recommendations of academicians, stakeholders started formulating mechanisms to fight child labor. Nevertheless, millions of children are still involved in many difficult activities, especially in the agricultural sector (ILO and UNICEF, 2022).

As an element of labor movement, migration is a global phenomenon that takes place across the world, primarily from the least developed to the most developed countries. The magnitude of migration from least-developed countries, such as Ethiopia, has been increasing across time owing to social, human made and natural factors (Sitompul, 2023). Reports indicate that the number of international migrants in 2020 reached 272 million, which is about 3.5 percent of the world's population (McAuliffe, 2022). These migrants sent money back home, where the remittances can support development and growth because they can be used as both foreign currency for capital goods purchases and as domestic income to increase savings (Glytsos, 2002). An estimated 1.3 million Ethiopian migrants send about USD 5 billion annually back to their family of origin, an amount more than 5 percent of the country's gross domestic product (GDP) and about 25 percent of its foreign exchange earnings (UNCDF, 2021). However, about 78 percent of Ethiopian migrants send money using informal networks (Esser & BCooper, 2020).

Migration, along with its drivers, and impacts on the socioeconomic development of migrant-sending areas and the welfare of household members left behind have become the focus of much debate in policy, academic, and political spheres (Obi et al., 2020). However, many studies about the impact of migration emphasized on topics different from child labor. According to Taye et al. (2019), migration plays an important role in improving the income of households that have migrant members . Another study about the impact of migration also confirmed that migration helps improve rural livelihoods through income diversification (Rigg et al., 2016). Another study shows that the contribution of migration to improving urbanization is also considerably high, as it energizes urbanization around the world (Raj and Raj, 2022). Narayan and Kankanhalli (2021) noted that along with financial income, migration brings social remittances such as changes in lifestyles and consumption patterns of recipient communities. Furthermore, many studies on migration income (remittance) in Ethiopia have examined its effects on household welfare in rural areas (Andersson, 2014), economic growth and poverty reduction (Abel, 2019), inequality, household consumption and investment (Sera, 2016), economic development (Redehegn et al., 2019), and food security (Abadi et al., 2018).

Even though the number of research and publications on migration in Ethiopia and elsewhere has increased, the bulk of them focus on the advantages of migration, which are related to social lifestyles, income, consumption, and production. Therefore, the impact of migration income on child labour in rural areas of developing countries like Ethiopia has been rarely unlocked, which creates a gap in our knowledge of the issue. This study, therefore, aims to address the impact of migration on child labour in rural areas of Ahun Tegegn and Raya Kobo Districts of North Wello, Ethiopia.

2. Materials and methods

2.1 Description of the study areas

North Wollo zone, which lies between latitudes of 11.92° or 11° 55' 12''N and longitudes of 39.1° or 39° 6'E, is 12,706 square kilometers in size. Of that area, 47.3% is degraded, 24% is arable, 17.4% is shrub-land, 4.6% is pasture, 0.37% is forest, and the remaining 6.3% is used for all other purposes (Kassegn and Abdinasir, 2023). The administrative center of the zone is Woldiya Town, which is 520 kms away from Addis Ababa along the main road to Mekelle and 360 kms from Bahir Dar. The dominant economic activity of this zone, like other parts of Ethiopia, is agriculture which varies from the hot and dry lowlands of about 1000 meters above sea level, via the fertile middle lands, to the cold highlands, with settlements reaching as high as 3700 meters above the sea in the Gedan-Bugna borderland, and this zone poses development challenges, because of its varied territories, and difficulty to reach its large areas (Ayalew, 2011).

The districts of North Wollo Administrative Zone are divided into four Livelihood zones based on agroecological setting, cultivation practices, and seasons, and crop and livestock types.These are: the North Wello East Plain Livelihood Zone(NWEP), the Northeast Weynadega mixed cereal livelihood zone(NMC, the North Wello Highland Belg livelihood zone (NHB), and Abay-Tekeze watershed livelihood zone(ATW). Raya Kobo district from NWEP and Angot district from NHB livelihood were selected fro the study based on their variations in livelihood activities.

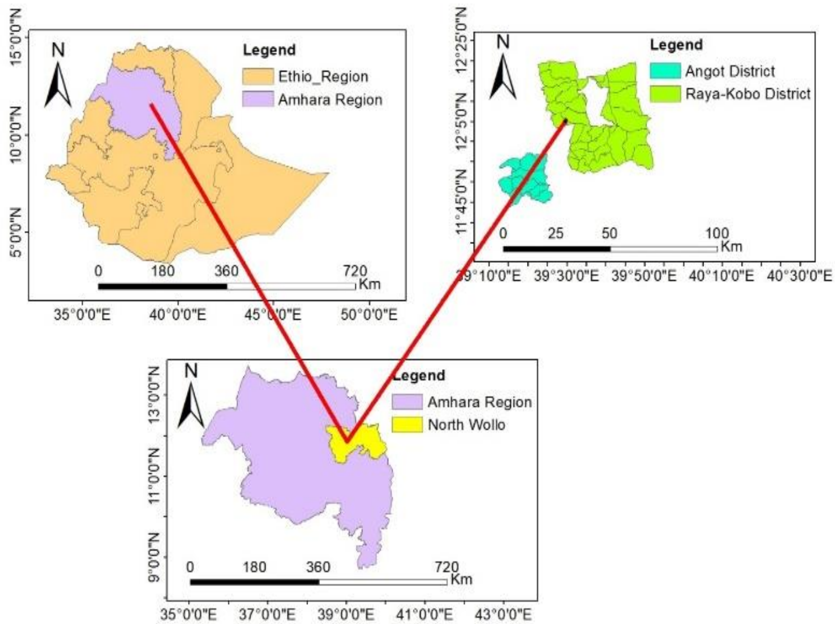


*Figure 1: Geographic location of Study (*Source: Raya Kobo & Ahun Tegegn District Agricultural Offices, and Authors' Calculation, 2021/22).

2.2 Data sources

Both primary and secondary data were used in the study. The main sources of primary data will be household head respondents and other key informants (experts form zonal and district child offices, education offices, police offices, representatives of NGOs, and local elderlies). Secondary data sources will include official reports, policy documents at different levels of administration, relevant research outputs of journal articles, books, and so on.

2.3 Study design and approaches

Studying the impact of migration on child labor in rural areas requires a robust research design and approach to gather relevant data and draw meaningful conclusions. Therefore this study considered pragmatism as the research approach/paradigm guiding this work, as it allows the collection and analysis of data on complex issues such as child labor that require coordination among relevant actors (Creswel, 2009). A mixed research design was also adopted for the study.

2.4 Sampling design (size and technique)

Using a multistage approach, random sampling technique was applied to select study areas and samples. In the first stage, North Wello zone, which has four livelihood zones, was purposively selected for this study from other administrative zones of Amahra region, as it is the most drought prone zone of the same (Ege and Adal, 2002), and it has a relative accessibility to the researchers. In the second stage, two livelihood zones were purposively selected from all available zones: the North Wello East Plain Livelihood Zone and the North Wello Highland Belg Livelihood Zone. The selection criteria included factors such as crop production practices, cropping seasons, types of crops and livestock, and production seasons, as well as agro-climatic conditions. Next, Raya-Kobo and Angot Districts were randomly selected to represent their respective zones, using stratified random sampling. Finally, four kebeles were randomly chosen from Ahun Tegegn and Raya-Kobo districts.

A systematic proportionate sampling technique was used to obtain samples, using the lists of individuals as a sampling frame. Men and women-headed households were represented in samples. Finally, 340 sample household heads from Raya Kobo District (21 men and 119 women) and Angot District (45 men and 15 women) were randomly selected making the total to be 400 households from the total population of 5199 households based on Yamane (1967) formula , given by. n=N/ (1+N (e2)); where, n = the desired sample size; N = total number of population and e = the level of precision or the quality of being accurate which is equal to 0.05. To account for non-response rate, the sample size was increased by 20 percent making the final sample size to be 480. The selection processes are presented in Table 1.

Table 1: Sample size

District	Population size		Kebeles	Total Household size		Sample size		Proportionate sampling formula to determine sample size of each kebele
Raya Kobo	MH	41932	Zobil 035	MH	994	MH	87	**$C_i = (C_i*n)/N$;** $C_{i=}$ Population size of each District and Kebele n = Total sample size N = Total population of the two Districts
				FH	461	FH	40	
	FH	26268		TH	1455	TH	127	
			Aradum	MH	1350	MH	134	
	TH	8200		FH	799	FH	79	
				TH	2144	TH	213	
Angot	MH	9141	Tesfa Giorgis	MH	700	MH	27	
				FH	300	FH	11	
	FH	2816		TH	1000	TH	38	
			Kosoamba	MH	500	MH	18	
	TH	11957		FH	100	FH	4	
				TH	600	TH	22	
Total		80157			5199		400	
Grand Total Sample Size = 400 +20perecent of it = 480								
MH= Male-headed household FH= Female-headed household TH = Total household heads								

Source: Authors' calculation prepared for this study, 2021/22

2.5 Methods of Data Collection

Numerous techniques of data collection were used. Hypothetical assumptions of pragmatism on the core issue of the research, i.e., like child labor, which is increasingly seen as a research perspective was used to guide the process of the research (Morgan, 2007; Creswell, 2009). Primary and secondary data were used in this study. Data collection techniques, such as desk/document review, structured/semi-structured interview, key informant interviews, focus group discussions (FGD), and participant field observations were utilized.

2.6 Data analysis

Data were analyzed using both descriptive (frequency, mean, percentage, and graph) and inferential statistical techniques (propensity score model). Since the propensity score matching (PSM) method does not require baseline data, unlike other non-experimental methods, it was used to measure the effect of migration on child labor. Propensity score matching is a necessary component of empirical estimates about the effect of migrations on beneficiary households based on cross-sectional data (Clément, 2011; Bertoli and Marchetta, 2013). This is because the matching method addresses the issue of having an appropriate instrument and a strong candidate for a dependable instrument (Rosenboum, 2005; McKenzie, et al.,, 2010). By creating a propensity score index for the treated and control groups to match, propensity score matching (PSM) reduces the multidimensionality matching challenge to one-dimensionality and provides improved non-experimental estimates in self-selected households of the intervention (Dehejia and Wahba, 2002; Deininger and Liu, 2009). Unlike parametric/regression models, PSM permits the assessment of mean impacts without fickle (depending only on data) assumptions on functional forms and error distribution (Jalan and Ravallion, 2005). This means that mean impacts can be estimated without any erratic assumptions about data-driven methodologies.

Another merit of PSM in estimating average treatment effects is balancing tests that do not involve the outcome variable to check the counterfactual precision of the control group to the treatment group (Lee 2008). PSM involves categorizing observations into two groups: the treated group that participated in the treatment (migration participant households) and the control group that did not participate the treatment (migration non-participant households). On the above explanation, treatment “T” is a binary variable that defines whether observations are treated or not. Accordingly, the value of “T” for treated observations is “1”, and “0” otherwise. The potential outcome of interest for household i is Yi1 if household i participates in migrations and Yi0 otherwise. Given these definitions, the impact of the treatment Ti on household i is given by logit model to estimate the PSM model with D (child labor in this study) as an outcome variable.

Matching can be performed conditioning on P(X) alone rather than on X, where P(X) = Prob (D= 1|X) is the probability of households participating in migration conditional on X, (Rosenbaum and Rubin, 1983). If outcomes without the intervention are independent of participation given X, then they are also independent of participation given P(X). A Logit model was used to estimate propensity scores using a composite of pre-intervention characteristics of sampled households (Rosenbaum and Robin, 1983) and matching performed using propensity scores of each observation.

Measurement of variables and hypothesis

Child labour (wt_chwt)

This is an outcome variable referring to children’s weekly working time. It is measured by the number of children’s weekly working hours at the household level. The hypothesis was if households participate in migration, children’s weekly working time will reduce, which indicates children’s reduced vulnerability to child labor.

Participation in migration (mig_familym):

This is a treatment (dummy) variable of the Logit model and assumes a value of 1 for households with migrant family members and 0 otherwise.

Covariates

Covariates refer to the observed attributes that are utilized to match participants between the treatment and control groups. These covariates included variables thought to affect both migration decisions and the results of child labor. Table 2 provides a brief summary of these factors that were anticipated to have an impact on the treatment variable in the rural regions of Ahun Tegegn and Raya-Kobo Districts.

Table 2: A summary of the specification of covariates that affect migration

Variable codes	Variable definitions	Type of variable	Expected sign
Distance to town	Distance b/n child's home & town	continuous,	+
Education status	Education level of household heads	continuous	-
Household head's sex	Gender of household status	dummy	+/-
Household size	The number of family members in a household	continuous	-
livestock in Tropical Livestock Unit (TLU)	The value of livestock in TLU	continuous	+
Annual loan	Annual credit gained in 2021	continuous	-
Diversification	Household's crop diversification	continuous	+
Input cost	Agricultural input cost	continuous	-
Crop land area	crop land area of a household	continuous	+/-
Household structure	Household marital structure	dummy	+/-
Annual revenue	Households' total anuual revenue	continuous	-
Age	Age of household heads	continuous	+/-

Source: Authors' specification and definition of variables for this study, 2021/22

Qualitative data that were from Focus Group Discussions (FGD), key informant interviews, and field Observations were analysed using qualitative analysis tools. The research results were based on common expressions and views shared by key informants and FGD participants. Besides, special care was also given to uniquely perceived but insightful expressions of focus group discussants or key informants. These were used as indicators to complement the quantitative data analysis.

3. Results and discussion

3.1 Demographic characteristics of sample households

This sub-section provides a summary of sample households' demographic and socio-economic characteristics. Information about households' demographic characteristics helps us capture and construe the findings of the survey. Results of the descriptive statistics in Table 3 shows that the average age of sample households is 64.6 years, indicating that most households are within the productive workforce. Concerning the education level of sample household heads, we found that the average number of years household heads spent in schooling is three, indicating the low level of education of households in the study areas.

Table 3: Socio-economic characteristics of sample households in Raya Kobo and Angot Districts in 2021 (N=431)

Items	Minimum	Maximum	Mean	Std Deviation
Age of household head	27	96	64.9	14.6
Education level of household heads	0	17	3.3	4.1
Distance to District towns in hours	0.58	6	2.7	87.1
Family size	2	19	6.4	2.1
Children's work starting age	5	16	6.8	1.4

Source: Own survey data collected for this study, 2021/22

The average walking time to reach the respective district town from household's residence is nearly two and half hours. Data on the prevalence of children's work indicate that there exists a very high prevalence of children's participation in domestic and field-based activities in rural areas of both districts (Raya-Kobo and Ahun Tegegn) starting from the age of five. Nearly all sample households confirmed that they participate their children (whether enrolled in school or not) in household tasks as deemed necessary.

3.2 Characteristics of children in rural areas

Children in rural areas engage in a variety of home, marketing, and outdoor activities. They help out around the house by cooking, cleaning, caring for babies, and doing laundry. Ploughing, harvesting, fencing, herding, fertilizing, weeding, cultivating crops, gathering wood, and fetching water etc., are some field tasks. These activities are typically organized by youngsters' gender. While girls are entirely responsible for domestic chores, such as cleaning, cooking, and babysitting, boys do perform field-based activities, such as ploughing, fertilizing, harvesting, and fencing. Both sexes share responsibilities for other household duties like marketing, gathering wood, farm maintenance, fetching water, and herding as well (graph 1, appendix A).

3.3 Livelihood activities, patterns of migration and its income

3.3.1 Livelihood activities, and patterns of migration

The research points to the fact that in the districts of Raya-Kobo and Ahun Tegegn, agriculture remains the main rural employment provider for children entering into rural labor force. Farming activities carried out to produce food crops, fruits, and livestock and others continued to be the most popular livelihoods sub-sector, among respondents in Raya Kobo District, accounting for 95% of all respondents. Agricultural activities serve as the main source of food, employment opportunities, and raw materials. In addition to meeting other demands, the production of crops and the rearing of livestock meet fundamental nourishment needs. Among the labor-intensive activities that farmers perform daily in agriculture are tilling the land, planting seeds, caring for plants, and maintaining livestock. The results of this study are supported by that of prior studies. Underdeveloped countries rely on agriculture to provide not only their basic requirements but also raw materials for their agro-based factories. It also generates foreign exchange, and increases rural welfare and farmers' purchasing power (L. Praburaj, 2018).

The results of the study on the patterns of migration indicated that most migrants (94 percent of 145 migrants) prefer informal (migration via illegal channels) migration routes instead of formal migration lines. That almost all migrant individuals from Raya-Kobo and Ahun Tegeng Districts are illegally migrated to the Middle East. Based on results in Table 4, there is a significant proportion (about 145 or 33.64 percent of 431) of households with migrant household members. This implies that there are nearly three households with migrant family members in every ten households in Raya Kobo and Ahun Tegegn Districts according to our survey results. Comparing the intensity of international migration across districts, Raya-Kobo district accounts for higher (135 or 93.1perecent of 145) number of global emigrants compared to Ahun Tegegn District. Regarding migrants' destination countries, almost all migrants (94.29 percent) preferred Middle East (mainly Saudi Arabia) as their destination country of work. The findings of the study is supported by previous studies conducted on the same topic. Aschalew (2021) found that there are frequent phenomena of rural-urban domestic migration in Ethiopia. Besides, Ethiopia is among the countries which face cross-boundary or global migration of active labor force in sub-Saharan Africa(Fikadu et al., 2020).

Table 4: Key livelihood occupation, destination country of migrants, patterns of remittance in Raya Kobo and Angot districts

Households with migrant household members	431	145	34%
No of migrants from Raya Kobo District	145	135	93.1%
No of migrants from Ahun Tegegn District	145	10	6.9%
No of Migrants who went to Saudi Arabia	145	135	93. 1%
Migrants who went to other countries	145	10	6.9%
No of Raya Kobo Migrants who went to Saudi Arabia	135	131	97.04%

No of Ahun Tegegn District Migrants who went to Saudi Arabia	10	4	40%
No of migrants who followed informal migration lines	145	136	94%
No of migrants who followed formal migration lines	145	9	6%

Source: Own survey data collected for this study, 2021/22

Eighty percent of migrants were committed in sending money home, according to an analysis of how people behave when sending money to relatives they have left behind. Raya Kobo District is home to almost 97 percent of the 116 migrants who send money back to their parents. Ahun Tegegn District is also home to the remaining 2.6 percent of migrants who send money home to support their family members (Table 5).

Table 5: Migrants' status of sending money to their left behind in Raya Kobo and Angot Districts in 2021.

Items	Total no of migrants	Remitting migrants	
Migrants who send remittances to family	145	116	80%
Raya Kobo Migrants who send remittances	135	113	97.4%
Ahun Tegegn Migrants who send remittances	10	6	2.6%

Source: own survey data collected for this study, 2021/22

3.3.2 Estimation of income inflows from migrants in 2021/22

Although some migrants did not send any money back to their place of origin, our survey indicates that the highest amount of migration revenue that emigrants sent to their family in 2021/22 was about 500,000.00 Ethiopian Birr (about USD 8333). In addition, the average migration revenue received by each household in 2021/22 from their migrated household members was nearly 24,294.3 Ethiopian Birr (nearly USD 405), while the total amount of migration money received by both districts in 2021/22 from 116 migrants was10,470,000.00 birr

(USD 174,500). The findings of previous studies support the results of this investigation. According to one study (Kefale and Mohammed, 2020), migrant workers from Ethiopia send large sums of money home to support or invest in their families. It was also discovered that Ethiopia is among the primary destinations of remittance inflows in East Africa (Zerihun, 2020).

3.4 The effect of migration on household livelihoods

The findings on the relationship between owning various household items, including radios, beds, carts, and livestock, and migration indicate that migration enhances a household's asset holdings. Consequently, the transcontinental migration leads to a notable difference in improved ownership of various household assets (Table 6). When radio ownership is broken down by migration status, it becomes clear that more households with migrant household members-95 had radios. Conversely, the larger proportion (nearly 90 percent) of households with non-migrant family members did not have a radio. In terms of bed possession, the empirical evidence in Table 6 displays a similar result. While a few (27 of 145) households with migrant household members confirm not having sleeping beds, most (148 of 286) households with non-migrant family members claimed the absence of sleeping beds in their homes. Moreover, according to the empirical results of this study, migration was found to have significant roles in enhancing households' possession of different household assets, like television, carts, and livestock. Most households with migrant family members asserted that they have household assets such as satellite television, carts, and livestock, while most households without migrated family members did not. These findings are buttressed by several earlier studies. Findings from Kangmennaang et al. (2017) indicate that families with migrant members accumulate household assets more positively. Additionally, research finding by Teferi (2016) revealed that migration enables the remaining family members to own a greater quantity and higher quality of consumer durables, further reinforcing the findings of this research.

Table 6: The contribution of migration to household assets

Items	Migration status of household members			Chi-Square (X^2)
Radio	Not migrated	Migrated	Total	$X^2 = 146.52$ Prob = 0.0000
No	258	50	308	
Yes	28	95	123	
Total	286	145	431	
Beds				$X^2 = 43.78$ Prob = 0.0000
No	148	27	175	
Yes	138	118	256	
Total	286	145	431	
Satellite Tv				$X^2 = 40.21$ Prob = 0.0000
No	208	60	268	
Yes	78	85	163	
Total	286	145	431	
Carts				$X^2 = 10.64$ Prob = 0.0011
No	194	75	269	
Yes	92	70	162	
Total	286	145	431	
Household's livestock number				$X^2 = 12.48$ Prob = 0.0004
14 and below that	194	73	267	
15 and above that	92	72	164	
Total	286	145	431	

Source: own survey data collected for this study, 2021/22

Household member migration has the potential to enhance rural livelihoods by increasing household income, as well as consumption and investment expenditures. Particularly, because they have additional sources of income from remittances, households with a migration status can spend more on overall consumption, which includes food and non-food expenses. The study's findings, which are based on annual household income and spending patterns of households in the study areas, demonstrate that, in comparison to households without migrant family members, households with migrant family members not only have higher incomes but also higher levels of consumption. The results of this study are further supported by Murad's (2016) research, which showed that migration generates significant income from migrant household members benefits the left-behind household members. More recently, the findings of Hossain and Gani (2022) found that migration has a favourable impact on improving household well-being by raising household consumption expenditures.

Regarding basic service access, a small percentage of households (95 of 286) with non-migrant household members had access to electricity, compared to over half (79 of 145) of households with migrant household members. The empirical investigation that compared households based on migration status also revealed a similar outcome regarding access to individual pipeline water services. While more households (174 out of 286) without any migrant family members lack access to individual pipeline water services, a greater proportion of households with immigrant household members had private pipeline water sources. Additionally, the results of the study on how migration affects the size of households' living homes show that the majority of (104 out of 155) households with migrant families have larger-sized homes. Still, many (186 of 286) households without migrant families have small-sized living homes. The results of this study are supported by the findings of prior studies, as it was found that households with migrant members better improve their basic services, as indicated by the findings of research by Kangmennaang et al., (2017).

3.5 Association between migration and child labor

The number of working children in families with non-migrant family members decreases when the weekly working hours category moves from low to high, as shown in Table 7's second, third, and fourth columns. Most non-migrant households (129 out of 286) stated that their children's involvement in domestic chores falls within the 21–40 hour weekly working hours category. Conversely, the number of household heads with migrant households rises in tandem with the number of hours worked by children each week. This number reached its highest point at 83 out of 145 in the weekly working category of hours 61–85 hours (Table 7). When one or more members of a household migrate, the amount of human labor in the household diminishes. This decrease in the productive labor force would result in a labor shortage within the family, and in rural areas, unskilled child labor inappropriately replaces the lost adult and skilled labor. Pearson's chi-square value 204.4201, which is significant at a one percent level (pr = 0.000), indicates that migration has brought a significant difference in the weekly working hours of children.

Table 7: The Relationship between households' and Children's weekly working hours in Raya Kobo and Angot Districts in 2021/22

Children's weekly working hours	Migration status of households			Chi-square (X^2)
	Non-migrant	Migrant	Total	X^2 = 204.4201 Pr = 0.000
below 13 hours	3	0	3	
13-30 hours	62	3	65	
31-48 hours	153	13	166	
49-66 hours	56	46	102	
67-85 hours	12	83	95	
Total	286	145	431	

Source: Own survey data collected for this study, 2021/22

3.6 The Impact of migration on the left-behind children: Econometric analysis

The propensity score matching model (PSM) was employed to analyse the impact of global migration on child labor in rural households of the study areas. We have therefore conducted each procedure of the model sequentially. The steps we performed were categorized into two parts. The first part is a validation of assumptions, and the second part is conducting the propensity score model using the best matching algorithm (see annexes 2, 3, 4 and 5).

3.6.1 Validation of assumptions

Selection based on observables

According to this assumption, who receives the treatment is entirely determined by observable characteristics, not by unobservable ones. However, there may be unobservable factors affecting treatment and control groups. This would imply that assumptions based on observables may not always hold and may not always be validated empirically. The key reason is treatment groups are not assigned randomly and may not always be the same as the control group on average, since there would be omitted variables. So, the research may only make a conceptual argument for why we think that observable characteristics are sufficient to explain the impact of the treatment.

The common support condition

The common support assumption implies that households' probability of being a migrant-sending family (treatment) for each possible value of X is strictly within the unit interval as is households' probability of not being a migrant-sending (control). In other words, the common support region shows that there are "control" individuals with similar characteristics as "treatment" individuals. This allows making comparisons between the two groups and validating the common support region using survey data collected for this study. It can be validated by first calculating the predicted propensity score values and then by plotting these values for control and treatment groups and observing if both overlap.

3.6.3 Chi-Square for the joint significance of variable, estimating treatment effect on the treated, and Sensitivity analysis

The test of joint significance for kernel 0.01 bandwidth matching results indicates fairly low pseudo R^2(0.265) value and likelihood ratio tests (145.7), which is significant at 1perecent level before matching. After matching, the value of pseudo R^2 became extremely low (0.009), and the likelihood ratio test was also found to be very low (2.84) and became insignificant (Table 8). These are concrete pieces of evidence that both treated and control groups have a similar distribution in all covariates after matching. These results clearly showed that the matching procedure effectively balances the two groups (migration participants and non-participants) of households. The different series of tests which we performed so far confirm that the chosen matching method was relatively the best to estimate the collected data. Now, the remaining task of the model is estimation of average treatment effect (ATT/ATET) of treated sampled households and conducting sensitivity analysis.

Table 8: Chi-square for the joint significance of variables, average treatment effect on the treated on children's weekly working time, and sensitivity analysis

Sample	**Pseudo R2**		**LR Chi 2**	**P >Chi2**	
Unmatched	0.265		145.75	0.000	
Matched	0.009		2.84	0.993	
Average Treatment effects on the treated (ATT)					
Outcome variable	treated	control	Difference	SE	t-value
Child labour	63.446	51.249	12.197	2.13	5.70***
Sensitivity analysis using Rosenbaum bounding approach					
Outcome variable	$e^{y}=1$	$e^{y}=1.25$	$e^{y}=1.5$	$e^{y}=1.75$	$e^{y}=2$
Child labor	P< 0.00	P< 0.00	P< 0.00	P<0.00	P< 0.00

Source: Authors' estimation collected for this study, 2021/22

e^{y} *(Gamma) Log odds of differential assignment due to unobserved factors where Wilcoxon significance level for each significant outcome variable is calculated.*

The ATT focuses on utilizing the PSM model to assess how the treatment variable (participation in migration) affects the outcome variable (child labor) in treated (migration participant) households. The estimation result offers a proof that migration affects child labor in a statistically meaningful way (Table 8). According to the average treatment impact on the treated (ATT), children from migration participant families have longer weekly working hours (about 12.2 weekly working hours) than children from migration non-participant households do, because of migration.

3.6.4 Sensitivity analysis

Sensitivity analysis is used to determine whether hidden bias exists. Hidden bias can arise when unobserved variables influence both the outcome variables and treatment assignment at the same time (i.e., could unobserved covariates alter treatment inference?). Sensitivity analysis, then, aids in assessing the degree to which unmeasured variables influence our selection procedure to mitigate the effects of matching (Caliendo and Kopeinig, 2008). The most important thing to understand about the matching process is that the matching estimators are biased against this unseen bias. Since non-experimental data cannot be utilized to quantify the scale of selection bias, we employed the bounding approach of Rosenboum (2005). Results in Table 8 discloses that the inference for the impact of global migration on child labor in rural households is not changing though migration participants and non-participant households have been allowed to differ up to 100 percent (2). That means for outcome variable (child labor) estimated at various level of critical values, the p critical values are significant suggesting the importance of covariates that affected both participation and outcome variables. This clearly indicates that our matching procedure for this study is free of hidden bias and child labor is solely determined by households' participation in migration, since the p-critical value (upper sigma value) at different critical value was 0 (zero). Thus, the sensitivity analysis in Table 8 concludes that impact estimates (ATT) are insensitive to unobserved selection bias and are pure impact of global migration.

The average treatment effect of the Propensity score model concerning the impact of migration on child labor, the result demonstrated that migration worsens child labor by increasing the working hours of children. It was found that the weekly working hours of children from households with migrant family members reach to about 63 hours, which is close to 11.2 hours more than that of children from households without migrant family members (see Table 8). When one or more members of a household migrate, the amount of human labor in that household diminishes. This decrease in the productive labor force would result in a labor shortage within the rural family, and unskilled child labor inappropriately replaces the lost adult and skilled labor.

Focus group participants indicated that one explanation for this finding is that households tend to prefer other financial objectives-owning domestic animals, building urban housing, and nurturing immigrants' children- to the welfare of their children. Focus group discussants also suggested that the current societal value of rural people to educated people mainly to teachers is too low to encourage children to learn. The finding of this investigation is consistent with the research results of Mendola (2016).

4. Conclusions and policy implications

4.1 Conclusions

Ethiopia has witnessed a surge in labor migration, particularly in its North Wello region, where there has been a significant outflow of the active labor force from the low-lying areas. The Raya-Kobo district serves as the focal point for such migration. One of the notable findings is that most migrants prefer Middle Eastern countries—especially Saudi Arabia—as their primary place of employment and residence. Furthermore, almost all migrants express a preference for using illegal migration channels over legal ones.

The results of this study also demonstrate that labor migration from rural areas, such as the Districts of Raya Kobo and Ahun Tegegn, can enhance household livelihoods by increasing household earnings, improving consumption patterns, and enhancing access to basic social amenities, such as private piped water. However, migration may also exacerbate child labor, primarily by extending the weekly hours that children must work.

4.2 Recommendations

As policymakers and stakeholders grapple with the implications of informal migration patterns, it becomes imperative to address the root causes behind the prevalence of informal migration and to develop comprehensive strategies that not only safeguard the rights and well-being of migrants but also foster conditions conducive to legal and regulated migration. The study's revelations serve as a crucial foundation for informed decision-making and targeted interventions aimed at reducing active labor force from the rural areas of Raya-Kobo and Ahun Tegegn Districts.

Policies and strategies aiming to create social awareness about adverse effects of participating children in child labor at their early ages, and implementing contextual legal corrective measures should also be part of policy reforms. To foster reduction of child labor in rural areas, reforms should consider about the role of remittances in the economy of rural households. One possible way is formulating policies that will help efficient utilization of remittances. For example, training and encouraging rural households to use remittances for both boosting investment drives, and children's wellbeing improvement activities (such as schooling, feeding, clothing, and health) in order to improve human capital in the long run.

Forthcoming studies should further investigate migrant and return migrants' socioeconomic evidence, the contexts of their stay in destination countries, key reasons of choosing destination countries, the patterns (estimated amount and frequency) in which migrants send money to the left behind families.

References

Abadi, N. *et al.* (2018) 'The Impact of Remittances on Household Food Security: A Micro Perspective from Tigray, Ethiopia', *WIDER Working Paper Series 040, World Institute for Development Economic Research (UNU-WIDER),* pp. 1–34.

Aktar Hossain, and M. O. G. (2022) 'Impact of migration on household consumption expenditures in Bangladesh using the coarsened exact matching (CEM) approach'. doi: 10.1108/AJEB-10-2021-0117.

Andersson, L. (2014) *Migration, remittances and household welfare in Ethiopia, UNU-MERIT Working Paper Series*.

Antonia Esser & Barry Cooper (2020) *Removing the barriers to remittances in sub-Saharan Africa: recommendations*. Bellvillie, South Africa.

Aschalew, A. (2021) 'Causes and Effects of Rural-Urban Migration in Ethiopia : A Case Study from Amhara Region Causes and E ff ects of Rural-Urban Migration in Ethiopia : A Case Study from Amhara Region'. Taylor & Francis. doi: 10.1080/00020184.2021.1904833.

Ayalew, G. K. (2011) 'School of Graduate Studies Institute of Development Studies (Ids) Dimensions and Determinants of Poverty Among', (May).

Bertoli, S. and Marchetta, F. (2013) 'Migration , remittances and poverty in Ecuador', *The Journal of Development Studies, Taylor & Francis (Routledge)*, 50(8), pp. 1067–1089.

Caliendo, M. and Kopeinig, S. (2008) 'Some Practical Gudance for the Implementation of Propensity score Matching', *Journal of Economic Surveys*, 22(1), pp. 31–72.

Clément, M. (2011) 'Remittances and household expenditure patterns in Tajikistan: A propensity score matching analysis', *Asian Development Review*, 28(2), pp. 58–87. doi: 10.2139/ssrn.2001145.

Creswel, J. W. (2009) *Research design : qualitative, quantitative, and mixed methods approaches*. 3rd edn. New York: SAGE Publications, Inc.

Dehejia, R. H. and Wahba, S. (2002) 'Propensity score-matching methods for nonexperimental causal studies', *Review of Economics and Statistics*, 84(1), pp. 151–161. doi: 10.1162/003465302317331982.

Deininger, K. and Liu, Y. (2009) 'Longer-term economic impacts of self-help groups in india', *World Bank Policy Research*, (WPS 4886), pp. 1–31.

Ege, S. and Adal, Y. (2002) *Farming Assets in North Wälo: Statistics, Maps and Impressions from a Travel to North Wälo*.

Fikadu T. Ayanie, Dagnachew T. Melese, Eyayew T. Beze, and T. A. F. (2020) 'Trends in Contemporary International Migration of

Ethiopia Trends in Contemporary International Migration of Ethiopia', (August). doi: 10.46404/panjogov.v1i2.2342.

Glytsos, N. P. (2002) 'The Role of Migrant Remittances in Development : Evidence from Mediterranean Countries 1', *Journal of ternational Migration*, 40(1).

ILO and CSA (2018) *The 2015 National Labur survey Ethiopia*. Addis Ababa, Ethiopia.

ILO and UNICEF (2021) *Child labour: Global Estimates 2020, Trends and the Road Forward*. New York.

ILO and UNICEF (2022) *Methodology of the 2020 ILO-UNICEF Global Estimates of Child Labour*. New York.

Jalan, J. and Ravallion, M. (2005) 'Household Income Dynamics in Rural China', *Insurance Against Poverty*, (November), pp. 1–28. doi: 10.1093/0199276838.003.0006.

Kangmennaang, J., Bezner-kerr, R. and Luginaah, I. (2017) 'Impact of migration and remittances on household welfare among rural households in Northern and Central Malawi', *Migration and Development*. Routledge, 2324(May), pp. 1–17. doi: 10.1080/21632324.2017.1325551.

Kassegn, A. and Abdinasir, U. (2023) 'Determinants of rural households ' livelihood diversification strategies : In the case of north Wollo zone , Amhara National Regional State , Determinants of rural households ' livelihood diversification strategies : In the case of north Wollo zone , Amha', *Cogent Economics & Finance*. Cogent, 11(1). doi: 10.1080/23322039.2023.2185347.

Kaur, N. and Ro. W. B. (2021) 'Prevalence and potential consequences of child labour in India and the possible impact of COVID-19 – a contemporary overview', *Medicine, Science and the Law*, 61(3), pp. 208–214. doi: 10.1177/0025802421993364.

Kefale, A. and Mohammed, Z. (2020) 'Migration, Remittances and Household Socio-Economic Wellbeing', *Migration, Remittances and Household Socio-Economic Wellbeing*. Addis Aaba, Ethiopia: Foreum for social Science studies, (14). doi: 10.2307/jj.8085386.

L. Praburaj (2018) 'Role of Agriculture in the Economic Development of a Country', *Shanlax International Journal of Commerce*, 6(July), pp. 1–5. doi: 10.5281/zenodo.1323056.

Lee, W. (2008) 'On Assessing the Specification of Propensity Score Models', (2007).

Majeed, M. T. and Kiran, F. (2019) 'Women's decision making power and child labor: evidence from Pakistan', *Quality and Quantity*. Springer Netherlands. doi: 10.1007/s11135-019-00864-y.

Marco De Gaetano, Francesco Caracciolo, Luigi Cembalo, and M. R. C. (2016) 'Effects of land related factors on child labour in agriculture: evidences from Peru', *Rivista di Economia Agraria*, 71(1), pp. 144–154. doi: 10.13128/REA-18635.

McAuliffe, M. and A. T. (2022) *WORLD MIGRATION REPORT 2022*.

McKenzie, D., Gibson, J. and Stillman, S. (2010) 'How important is selection? Experimental vs. non-experimental measures of the income gains from migration', *Journal of the European Economic Association*, 8(4), pp. 913–945. doi: 10.1162/jeea_a_00008.

Mendola, M. (2016) *How does migration affect child labor in sending countries ?* doi: 10.15185/izawol.286.

Murard, E. (2016) *Consumption and Leisure : The Welfare Impact of Migration on Family Left Behind*. Bonn.

Narayan, V. and Kankanhalli, S. (2021) 'The Economic and Social Impacts of Migration on Brand Expenditure: Evidence from Rural India', *Journal of Marketing*, 85(6), pp. 63–82. doi: 10.1177/00222429211021992.

Obi, C. *et al.* (2020) 'How does international migration impact on rural areas in developing countries ? A systematic review', *Journal of Rural Studies*. Elsevier Ltd, (June). doi: 10.1016/j.jrurstud.2020.09.016.

Raj, D. and Raj, M. (2022) 'Seasonal migration as strategy for livelihood diversification and environmental adaptation in Nepal', *African Journal of Social Work*, 11(3), pp. 81–90.

Redehegn, M. A. *et al.* (2019) 'Development impacts of migration and remittances on migrant-sending communities: Evidence from Ethiopia', *PLoS ONE*, 14(2), pp. 1–20. doi:

10.1371/journal.pone.0210034.

Rigg, J. *et al.* (2016) 'The puzzle of East and Southeast Asia ' s persistent smallholder', *Journal of Rural Studies*. Elsevier Ltd, 43, pp. 118–133. doi: 10.1016/j.jrurstud.2015.11.003.

ROSENBAUM, P. (2005) 'Observational Study', *Encyclopedia of Statistics in Behavioral Science*, 3, pp. 1451–1462. doi: 10.1007/978-3-211-89836-9_951.

ROSENBAUM, P. R. (2005) 'Sensitivity Analysis in Observational Studies Randomization Inference and Sensitivity', 4, pp. 1809–1814.

Rosenbaum, P. R. and Rubin, D. B. (1983) 'The central role of the propensity score in observational studies for causal effects', *Biometricca*, 70(1), pp. 41–55. doi: 10.1017/CBO9780511810725.016.

Sera, J. H. & L. (2016) 'Impact of International Remittances on Poverty Reduction in South-West Ethiopian: Evidence from Jimma Zone', *Jlobal Journal of Managment and Business Research: B Economics and Commerce*, 16(6). doi: 10.33182/rr.v4i1.556.

Sianesi, B. (2004) 'An evaluation of the Swedish system of active labor market programs in the 1990s', *Review of Economics and Statistics*, 86(1), pp. 133–155. doi: 10.1162/003465304323023723.

Sitompul, T. (2023) 'Economic and social impact of migration', *Journal of Accounting & Management Innovation*, 7(1).

Tenaye, A. (2019) *TThe Role of International Remittance on Economic Growth in Ethiopia*, *Journal of Population and Social Studies*. School og Graduate Studies, ST. Marry University. doi: 10.25133/JPSSv27n3.0015.

Teye, J. K. *et al.* (2019) *The impact of migration on the welfare of households left behind in rural Ghana : A quasi-experimental impact evaluation*. 62. Brighton.

United Nations Capital Development Fund (UNCDF) (2021) *Review of Remittance Policy , Legal and Regulatory Framework*. Ethiopia.

Yamane, T. (1967) *Statistics: An introductory Analysis*. 3rd edi. New York: Harper & Row, Publishers, Inc.

Zerihun, M. F. (2020) ‘Remittances and Economic Growth: Evidence from Ethiopia, Kenya, and Uganda’, *African Human Mobility Review*, 6(3), pp. 6–27. doi: 10.14426/ahmr.v6i3.912.

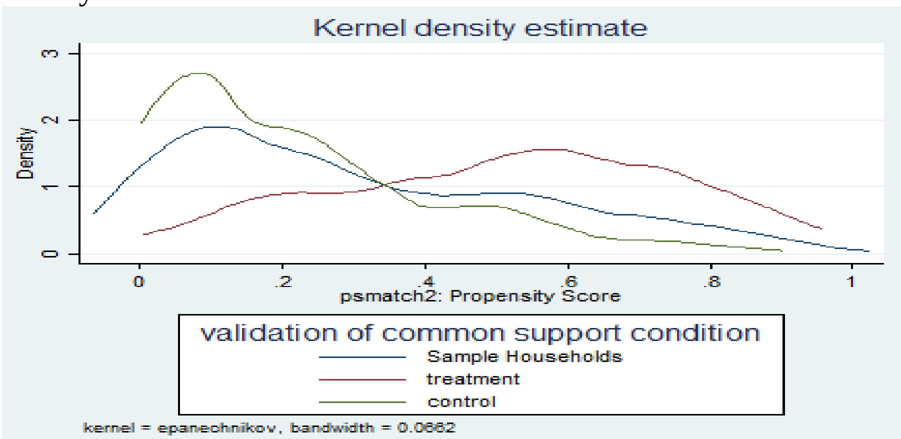
Appendix

Annex 1: A Probit regression model on the determinants of migration

mig_familym	Coef.	St.Err.	t-value	p-value	[95% Conf. Interval]		Sig
loan_dollar	.001	.001	2.06	.04	0	.002	**
town_distance_walking_hours	.09	.044	2.03	.043	.003	.176	**
gender_hh_heads	-.442	.215	-2.06	.04	-.864	-.021	**
education_heads	-.035	.039	-0.90	.368	-.111	.041	
age_heads	-.016	.025	-0.64	.523	-.066	.033	
househld_size	-.106	.064	-1.66	.097	-.231	.019	*
livestock_tlu	.002	.001	2.12	.034	0	.004	**
crop_diversification	.049	.051	0.96	.337	-.051	.149	
annual_saving	0	0	1.85	.064	0	0	*
crop_land_area	-.006	.027	-0.24	.814	-.059	.046	
household_structure	.311	.185	1.68	.093	-.051	.674	*
Constant	.267	1.843	0.14	.885	-3.344	3.878	
Mean dependent var		0.336	SD dependent var			0.473	
Pseudo r-squared		0.265	Number of obs			431	
Chi-square		145.76	Prob > chi2			0.000	
Akaike crit. (AIC)		428.75	Bayesian crit. (BIC)			477.54	
*** p<.01, ** p<.05, * p<.1							

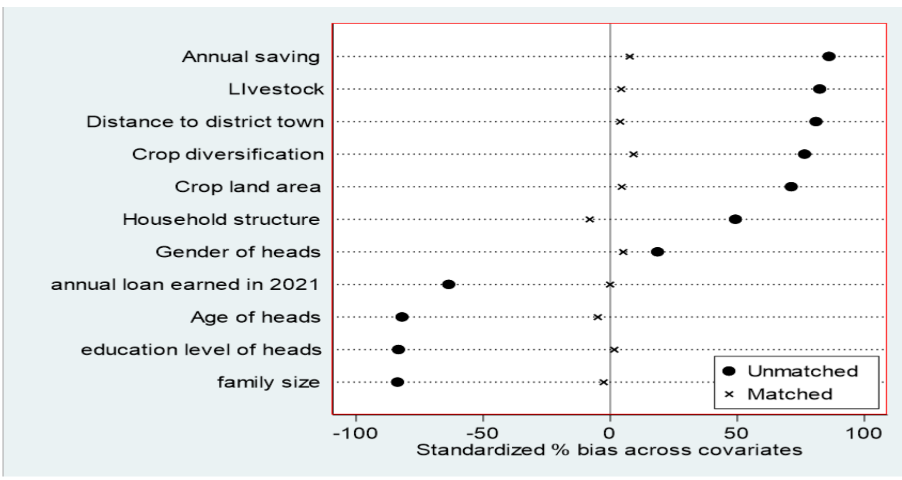
Source: Authors' estimation for this study, 2021/22

Annex 2: pscore distribution of treated and control households in kernel density estimate



Source: Authors' estimation for this study, 2021/22

Annex 3: Covariates distribution for matched and unmatched household characteristics



Source: Authors' estimation for this study, 2021/22

Annex 4 : Results of Logistic regression model on factors of migration in Raya-Kobo and Angot Districts

mig_familym	Coef.	Std. Err.	z	P>z	[95%Conf. Interval]	
loan_dlr_anual	0.001	0.001	1.500	0.135	-0.000	0.003
disth_town	0.135	0.072	1.870	0.061	-0.006	0.275
gender_heads	-1.050	0.361	-2.910	0.004	-1.758	-0.342
educ_head	-0.150	0.062	-2.410	0.016	-0.272	-0.028
age_head	-0.003	0.045	-0.070	0.942	-0.091	0.085
family_size	-0.196	0.108	-1.810	0.070	-0.408	0.016
Livestock (tlu)	0.004	0.002	2.530	0.011	0.001	0.007
diversific	-0.032	0.083	-0.380	0.702	-0.194	0.131
saving_anual	0.000	0.000	1.800	0.071	-0.000	0.000
crop_land_area	-0.007	0.045	-0.150	0.879	-0.096	0.082
hh_struct	0.629	0.315	1.990	0.046	0.011	1.246
_cons	0.094	3.220	0.030	0.977	-6.217	6.405

Logistic regression Number of obs = 431
LR chi2(11) = 112.35
Prob > chi2 = 0.0000
Log likelihood = -219.07562 Pseudo R2 = 0.2041

Source: Authors' estimation for this study, 2021/22

Annex 5: Matching process of variables using Kernel matching algorithm

```
. pstest, graph both
```

Variable	Unmatched Matched	Mean Treated	Mean Control	%bias	%reduct |bias|	t-test t	t-test p>|t|	V(T)/V(C)
loan_dlr_anual	U	63.234	232.36	-63.6		-5.78	0.000	0.34*
	M	75.155	91.092	-6.0	90.6	-0.58	0.564	0.81
disth_town	U	8.4156	6.6989	80.9		8.08	0.000	1.23
	M	7.9754	8.0196	-2.1	97.4	-0.16	0.871	0.89
gender_heads	U	.31724	.23427	18.6		1.85	0.064	.
	M	.35246	.34595	1.5	92.2	0.11	0.915	.
educ_head	U	1.3241	4.3427	-83.3		-7.68	0.000	0.43*
	M	1.5738	1.8415	-7.4	91.1	-0.67	0.505	0.83
age_head	U	57.545	68.675	-82.0		-8.03	0.000	0.99
	M	59.541	59.927	-2.8	96.5	-0.22	0.828	0.85
family_size	U	9.1448	11.874	-83.7		-8.15	0.000	0.91
	M	9.6066	9.7092	-3.2	96.2	-0.25	0.807	0.90
tlu	U	67.574	35.689	41.9		4.25	0.000	1.46*
	M	50.185	54.956	-6.3	85.0	-0.47	0.640	0.54*
diversific	U	6.6207	4.2063	76.4		7.48	0.000	0.97
	M	6.1148	6.0053	3.5	95.5	0.27	0.789	0.93
saving_anual	U	47888	28051	86.0		8.42	0.000	0.97
	M	44802	43748	4.6	94.7	0.36	0.719	1.11
crop_land_area	U	15.618	8.3881	71.2		7.14	0.000	1.31
	M	14.046	13.911	1.3	98.1	0.10	0.924	0.83
hh_struct	U	.86207	.65734	49.2		4.60	0.000	.
	M	.85246	.88215	-7.1	85.5	-0.68	0.496	.

* if variance ratio outside [0.72; 1.39] for U and [0.70; 1.43] for M

Source: Authors' estimation for this study, 2021/22