Effects of childhood work on long-term out-migration decision in rural Ethiopia

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We investigate the effects of childhood work on migration decisions and patterns later in life using a novel prospective panel dataset from rural Ethiopia. The data were generated through a follow-up tracking survey of 4-14-year-old children at baseline (1999/2000) after sixteen years in 2015/2016. We find that village out-migration was by and large dominated by females and schoolchildren. Compared to schooling-only, fulltime childhood work significantly reduces the probability of village out-migration later in life. In contrast, those who combined work and study at baseline were highly likely to engage in economic or employment out-migrations. Thus, we presented new evidence in the related literature that besides the existing rural to urban labor migration explanations, childhood conditions in a rapidly changing developing economy setting may also affect children's long-term migration decisions. The findings also suggest that elimination of full-time child labor should be a long-term human capital policy priority. However, excluding the worst forms of child labor, an attempt for child labor elimination in all its forms could be un(counter)productive. More importantly, rural child education seems to be as critical as enabling the future farm labor to shift from farm to non-farm activities and facilitate the structural transformation process.

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Keywords: Migration; Child Labor; Childhood work, Child schooling; Ethiopia

1. Introduction

The spatial and sectoral mobility of labor is an integral part of economic development and structural transformation processes. Labor migration can drive economic growth and help to reduce poverty (de Brauw 2015; de Brauw & Mueller 2012; Deshingkar & Grimm 2004) but also contribute for urbanization (Hailemariam & Adugna 2011; Todaro 1997), with all its pros and cons for economic development. It is no exception to Ethiopia where historically, either in organized or isolated instances, people migrated both within and across regions in response to farmland shortages, production difficulties and environmental pressure, and low economic opportunities. Accordingly, most of the past internal migrations in the country were from densely populated and farmland deficit areas, often parts of the highlands, to places where farmland is plentiful, usually the lowland areas (Ezra & Kiros 2001; FDRE 2003; Webb & von Braun 1994).

A number of factors characterize the recent internal labor migration in Ethiopia. Since 1991, the Ethiopian government embarked on series of economic and political reforms with momentous implications for rural labor out-migration. Among others, the government lifted the systematic and regulatory restrictions on labor mobility which was imposed by the Dergue regime on the grounds of security (Bigsten et al. 2000) and liberalized the road transport, trade, and rural labor markets (Abegaz 1999). As a result, the mobility of labor across occupations and economic sectors during the early 1990s seemed to be mainly induced by economic and institutional reforms, new economic policies, and subsequent improvements in the performance of the economy. Accordingly, in 1994 about 14.1 percent of the population (6.91 million individuals) was internal migrant which increased to about 16.6 percent (12.22 million) in 2007 (Kuffa 2014). Yet, both the transitional government (TGE) in the early 1990s and later the rural development policy and strategies discouraged rural to urban migration for it being rather "unproductive" move (FDRE 2003; TGE 1993). Further controls on isolated rural to rural migrations and large and unstructured resettlements were imposed due to potential negative consequences for the environment, inciting inter-ethnic conflicts, and their limited effects on food security (FDRE 2003). Even so, voluntary resettlement program is still considered as one of the ways to realize the national food security strategies (FDRE 2003).

As part of its wider efforts to end poverty and accelerate sustainable development, the government also made tremendous changes in the education sector, decentralized the administration system, invested in infrastructure, and reformed the service delivery. These and other changes might have both short-term and long-term effects on children, some effects being persistent and profound in children's development. For instance, in 1995/96, following the 1994/95 abolition of school fees, the overall primary school enrollment increased by about 23 percent (World Bank 2009). In the following years, the country saw considerable growth in net enrollment rate in the primary schools, increased from 27 percent in 1996/97 to 48.8 percent in 2000/01 (MoE 2002). However, Ethiopia has also one of the highest rates of child labor. The 2001 Ethiopian child labor survey indicates that about 42.3 percent of 5-14-year-old children work in productive and housekeeping activities, contributing about 34 hours of labor to the household productive activities per week (CSA 2002). Our study, therefore, was motivated to unravel the effects of the prevalence of pervasive child labor in the rural parts of the country under expanding child education on their future migration decision and patterns.

In this regard, despite the above economic and institutional changes, limited level of labor left the country's agriculture sector (World Bank 2016a). In more than two decades, the employment share of agriculture declined by about 5 percentage points since the 1990s, from 80 percent in 1990-1997 (IMF 1999) to 75 percent in 2015/2016 and expected to be about 67.5 percent by 2019/2020 (National Planning Commission 2016). As far as the returns to migration is concerned, on the contrary, recent evidence shows that the out-migration of labor from farm to the non-farm sectors led to improvements in the per capita income growth during 2005 and 2013 by about 25 percent (World Bank 2016b) which indicates enormous potentials of migration for poverty reduction. Other studies also find a substantial rise in consumption among migrants – about 110 percent compared to non-migrants (de Brauw et al. 2013). Our study provides further evidence in understanding this paradoxical situation – limited agriculture labor out-migration in the midst of higher potential migration returns.

Taking childhood work and education as alternative forms of parents' human capital investments in children, we identified the causal effects of childhood work on long-term village out-migration decisions. Using multi-valued treatment effects framework and a doubly robust estimation method to control observable factors, we find that full-time childhood work compared to schooling-only to a large extent reduces the migration decision when children grow up. Similarly, using childhood work index – a new approach in the related literature, we also find that compared to non-working children, those with high work index tend to stay in the villages later in life. A further analysis shows that combining work and study compared to work-only was positively and significantly associated with economic out-migration. We, thus, argued that childhood work when combined with schooling, in consonance with the human capital theory of migration (Sjaastad 1962), may have provided them the opportunity to acquire transferable and marketable skills during childhood and increased their tendency to out-migrate and work in non-farm economic activities when adults. Contrary to the risk and poverty hypotheses of migration (Stark & Bloom 1985; Stark & Taylor 1991), we did not find an increasing proportion of children from the poorest households compared to those from other household wealth groups in the aggregated migrant population.

2. Review of related empirical literature on Ethiopia

Previous empirical studies report various factors that could affect rural out-migration decisions and patterns in rural Ethiopia. Earlier studies indicate that population growth and insufficient access to food (Ezra & Kiros 2001), population to resources imbalances (Hailemariam & Adugna 2011), ecological degradation and drought (Berhanu & White 2000;

Ezra & Kiros 2001; Mberu 2006), and state-led resettlement and villagization programs in response to recurrent drought, famine and environmental degradation (Kassa 2004; Kloos & Aynalem 1989) contributed to the out-migration of labor in rural Ethiopia at different times.

Recent studies also show that rural out-migration of labor can be explained by credit constraints and agricultural productivity (de Brauw 2015), farmers' opportunistic behaviors due to emerging job opportunities in other areas (Hailemariam & Adugna 2011; Kassie & Aye 2017; Mberu 2006; Tadele et al. 2006), and overall destitution of households and poverty (Atnafu et al. 2014; Gebru & Beyene 2012). Studies also find that farmland scarcity mainly to the youth or lower productivity (Bezu & Holden 2014; Morrissey 2008), the need to diversify livelihoods (Gebru & Beyene 2012; Gibson & Gurmu 2012; Tadele et al. 2006), sibling competitions over limited household resources such as farmland (Gibson & Gurmu 2012), and natural catastrophes, war and pestilence (Mberu 2006) push labor from rural areas to migrate.

Drought continues to be one of the main causes of out-migration of farm labor from rural villages (Ezra & Kiros 2001; Gray & Mueller 2012; Morrissey 2008; Murendo et al. 2011). For instance, Ezra and Kiros (2001) find that rural out-migration from 1984 to 1994 was higher from communities that were perceived to be more vulnerable to shocks. In line with the idea of migration as a risk-sharing strategy (Stark & Bloom 1985; Stark & Taylor 1991), households in drought-prone areas also use migration to mitigate income risks (Gibson & Gurmu 2012).

Other socio-economic factors such as marriage (Ezra & Kiros 2001; Hailemariam & Adugna 2011), family dissolution, and religious activities may also lead to gender and age-differentiated rural out-migration. Through a tracking survey in rural Ethiopia, de Brauw and Mueller (2012) find that between 2004 and 2009, while less than 50 percent of the migrants left various Ethiopian rural villages for employment purpose, marriage was generally the main reason for outmigration. Several factors such as human capital level may distinguish migrants and the differences in migration purposes. In relation to this, de Brauw (2015) and Blunch and Ledechi (2015) find that better-educated individuals and those from wealthier households (de Brauw 2015) are more likely to participate in rural-urban or internal migration. Similarly, Tegegne & Penker (2016) also find that while short-term migration could be the result of location advantages and food insufficiency, households' human capital endowment may drive the long-term migration decisions. Although these studies assumed homogeneity in migrants' childhood conditions and still others proximate migration at the household level, their findings show the critical role of education in the internal migration process.

The debate also continues whether the current Ethiopian land tenure system triggers or inhibits rural labor out-migration in the country. Some studies argue that the current farmland tenure system discourages landholders from participating in rural to urban migration due to the fear of farmland confiscation by the local government (de Brauw & Mueller 2012; Rahmato 2004; Teklu 2003). On the other hand, Ezra and Kiros (2001) and Bezu and Holden (2014) assert that Ethiopia's land tenure policy triggers the out-migration of rural labor, mainly the youth. However, de Brauw and Mueller (2012) argue that improved farmland ownership may result in less outmigration of labor in rural Ethiopia. The evidence is still thin to conclude that the current rural land tenure system is an obstacle to the spatial and occupational mobility of labor (World Bank 2016a), although we cannot rule out the future effects of the land tenure system on labor out-migration. The government also believes that the land tenure system does not impede labor mobility, instead, the availabilities of land and rainfall and economic returns guide farmers' migration decisions (FDRE 2003). It further stresses that limited rural labor mobility could be explained by the meager job opportunities in the non-farm sectors and not due to the land tenure system (FDRE 2003).

However, no previous study to our knowledge examines the effects of human capital investment in children and childhood labor market participation on their long-term migration decisions in rural Ethiopia. We explore this and identify the causal effects of childhood work and schooling participation on rural village out-migration decisions later in life. For this purpose, we conducted a follow-up tracking survey to children in 1999/2000 after sixteen years in 2015/2016 and constructed a unique and novel prospective panel dataset.

3. Methods of analyses

3.1 Sampling design and sources of data

The paper uses a prospective panel dataset from rural Ethiopia; generated through a follow-up tracking survey using the Fifth round of the Ethiopian Rural Household Survey (ERHS) conducted in 1999/2000 as a baseline. The ERHS is a unique panel survey with seven rounds collected between 1994 and 2009 following well-spread households in rural Ethiopia. It was conducted jointly by Addis Ababa University, University of Oxford, and International Food Policy Research Institute (IFPRI). The fifth round survey covered 18 rural villages located in four major regions (Tigray, Amhara, Oromia, and Southern Nations, Nationalities, and Peoples' Region (SNNPR)). A total of 1,681 households were surveyed, constituting 8,924 individuals, of which 3,183 were 4-14-year-old children. After 16 years, in 2015/2016, we administered a follow-up tracking survey on 789 of these children from 326 re-sampled households. Unlike ERHS that follows the households, we followed children. For the sake of brevity and consistency, we refer these children as Resurveying Targets (RTs).

For the follow-up survey, out of 18 villages, we sampled five of them including Dinki, Shumsha, Debre Berhan villages, Adele keke, and Adado from which 326 households with 789 RTs were selected using stratified multi-stage sampling technique. However, some households and RTs were attired from the follow-up survey due to the migration of RTs alone or collectively with the entire households, death, or withdrawal from the follow-up survey. In this regard, 14 baseline households could not be traced with the entire member RTs, leading to a 4.3 percent household level attrition. As a result, the survey collected data from 312 households either through direct resurvey of the households or indirectly through either split-off RTs or RTs that joined other households. Furthermore, 137 RTs were not tracked due to death, far-off migration, and lack of consent to be resurveyed, thus we fully resurveyed 652 RTs (82.6 percent). We analyzed and found that there was no significant difference between the resurveyed and attired children in terms of their childhood work and schooling conditions. It is less likely, thus, that selection bias due to the attrition of RTs should be a concern. In the end, we collected data on a total of 2,268 individuals, constituting 1,192 new members, 705 continuing members, 329 split-off households, and 42 RTs as members of other households.

Thus, while the follow-up survey was administered to the tracked RTs (both migrants and non-migrants from baseline villages), we also collected basic data including migration reasons (although it could not be verified for attired RTs) and year of out-migration of those who could not be accessed to conduct the full survey. We used all children, both tracked and attired (764 children – excluding 25 deceased RTs after 1999/2000) with some information to analyze their out-migration decisions and further issues such as reasons for migration and migration destination were discussed using tracked RTs only (652 children).

3.2 Multi-valued treatment models

We treated childhood work participation as exposure to treatment and attempted to investigate its long-term causal effects on migration decision using conditional independence assumption (CIA). Unlike the binary treatment effects model introduced by Rosenbaum and Rubin (1983), treatments could also be multi-valued, ordered or continuous. Monte Carlo simulation analysis and empirical studies (Linden et al. 2016; Uysal 2013) show that when treatment is multi-valued doubly robust estimators (augmented inverse probability treatment weighting

(AIPTW) and inverse probability treatment weighting with regression adjustment (IPTWRA)) produce unbiased estimates even when either the treatment assignment or outcome equation is misspecified. Linden *et al.* (2016) also compared the performances of alternative methods to estimate the multi-valued treatment effects and they recommend these doubly robust methods – whereby both the treatment assignments and the outcome equation are estimated within the same framework (Linden et al. 2016). Therefore, following Imbens (2000) and Lechner (2001), and as proposed by Uysal (2013) and Linden *et al.* (2016), we applied IPTWRA to estimate the long-term effects of childhood work on the decision to out-migrate from the respective baseline villages.

3.3 Econometric model specification

The doubly robust weighting estimator for multi-valued treatment effects is specified based on Imbens (2000), Lechner (2001), Uysal (2013) and Linden *et al.* (2016). For a sample of N observations identified by i, $i=1,\dots, N$, we observe Y_i (the decision to migrate), T_i (multi-valued treatment - Childhood work indicator variables), and X_i (vector of pre-treatment covariates). We denoted the treatment indicator variable for child i receiving treatment t by $D_{i(t)}$ and expressed as:

$$D_{i(t)} = \begin{cases} 1, & \text{if } T_i = t \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

For child i and treatment value $T_i = t$, where $t \in \tau = \{0, \dots, K\}$, we have corresponding potential outcomes denoted by $Y_{i(t)}$, $(Y_{i0}, \dots, Y_{iK})$. Based on treatment value t, we observe only one potential outcome for each child. Thus, in line with Rubin (1974) potential outcomes framework, using the treatment indicator, $D_{i(t)}$, and potential outcome, $Y_{i(t)}$, and following Linden *et al*. (2016) we write the observed outcome, Y_i as:

$$Y_i = \sum_{t=0}^{K} D_{i(t)} Y_{it} \quad (2)$$

Accordingly, among several pairwise treatment effects (Lechner 2001), given two treatment levels, m and l, the average child-level effect of treatment level m versus l is given by Y_{im}-Y_{il}. The population average treatment effect using the two potential outcomes is computed as:

$$\Delta_{ml} = E[Y_{im} - Y_{il}] = \mu_m - \mu_l \quad (3)$$

The value Δml could have been estimated using the sample means of observed outcomes had we obtained the outcomes from a random experiment. However, in an observational study, estimating Δml requires additional conditioning on *Xi*, which is assumed to include all pre-treatment covariates associated with the treatment assignment and potential outcomes. By conditioning on *Xi*, the assumption is that our treatment assignment is as good as a randomization so that we replicate the randomization process (Linden et al. 2016). This assumption, also called weak unconfoundedness, as defined by Imbens (2000), can be formally stated as follows:

$$Y_{it} \perp D_{i(t)} \mid X_i, \quad \text{for all } t \in \tau \text{, where } \perp \text{ denotes orthogonality} \tag{4}$$

This requires that all X_i that affect the treatment level and the outcomes are observed is indeed a strong assumption. In combination with the unconfoundedness assumption – Rosenbaum & Rubin (1983) refer the combinations of unconfoundedness and overlap as strong ignorability, we also assume a complete overlap in the distribution of pretreatment covariates between treatment groups. The assumption is expressed as follows:

$$0 < \Pr\left[\mathrm{T_i} = t \mid X_i = x\right] \text{ for all } t \in \tau \text{ and for all } x \text{ in the support of } X \tag{5}$$

Under these assumptions, Imbens and Wooldridge (2009) specify that for treatment level *t*, the conditional expectation of the potential outcome using the conditional expectation of observed outcomes of those who received the treatment level and given covariates is:

$$E\left[Y_{it} \mid X_i\right] = E\left[Y_{it} \mid D_{i(t)}, X_i\right] = E\left[Y_i \mid D_{i(t)}, X_i\right] \tag{6}$$

$$= E\left[Y_i \mid T_i, X_i\right] \tag{7}$$

where averages of conditional means give us $\mu_t \equiv E\left[Y_{it}\right] = E\left[E\left[Y_{it} \mid X_i\right]\right]$, unconditional means. Alternatively, when treatment is multi-valued and X_i are high dimensional, conditioning directly on *Xi* can be conducted using generalized propensity score (GPS) approach (Imbens 2000). Imbens (2000) defines the GPS as '[…] the conditional probability of receiving a particular level of the treatment given the pretreatment variables' (Imbens 2000 p. 708) and expressed it as follows:

$$r(t, x) \equiv pr\left[T_i = t \mid X_i = x\right] = E\left[D_{i(t)} \mid X_i = x\right] \tag{8}$$

Through weighting the observed outcomes by the conditional probability of the received treatment *t*, one can also identify the means of potential outcomes as:

$$E\left[\frac{Y_i D_{i(t)}}{r(t, X_i)}\right] = E[Y_{it}] \tag{9}$$

Based on the nature of the multi-valued treatment variable we estimate the GPS, $r(t, Xi)$ by discrete response or ordered response models (Imbens 2000; Linden et al. 2016; Uysal 2013).

Linden *et al.* (2016) proceed in their Monte Carlo simulation analysis and specified the AIPTW estimator. Having the conditional independence and strict overlap assumptions in mind, the AIPTW unconditional mean is estimated as follows:

$$\hat{\mu}_t^{aipw} = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{Y_i D_{i(t)}}{\hat{r}(t, X_i)} - \frac{D_{i(t)} - \hat{r}(t, X_i)}{\hat{r}(t, X_i)} \hat{m}_{t(xi)}\right] \tag{10}$$

Accordingly, the unconditional mean is estimated using the estimated GPS from the first step, $\hat{r}(t, X_i)$ and estimated conditional mean functions, $\hat{m}_{t(xi)}$. The contrasts of these weighted averages provide the estimates for the ATE (Linden et al. 2016).

We reported IPTWRA results which estimate the GPS using the treatment model and combines it with the outcome model. Like AIPTW, IPTWRA also generates the estimates for the treatment model and computes the weights as the inverse of the GPS, i.e. $D_{i(t)} / \hat{r}(t, X_i)$ for each treatment value. Then, for each treatment level, using the estimated inverse probability treatment weight, the regression adjustment is fitted by a weighted regression for the outcome model. Using the estimates from the weighted regression, it obtains the treatment-specific predicted outcomes. Lastly, it computes the means of the treatment-specific predicted outcomes – thereby the ATEs is the contrasts between these averages (Linden et al. 2016).

4. Results and Discussion

4.1 Childhood work characteristics

Table 1 illustrates childhood work[1] and schooling characteristics grouped by child age cohort, the birth order among 4-14-year-old siblings, and gender. The baseline data shows that quite a high proportion of children were exclusive workers, twice as much as those who combined

[1] *While the descriptive section will be explaining the combinations of work and schooling, later we introduced a new childhood work measurement, childhood work index, constructed using principal component analysis from a wide array of child labor indicator variables.*

work and study. However, from a gender perspective, while boys were slightly more likely to either school-only (albeit fewer children were found in this group) or combine it with work compared to girls, the latter tend to be full-time workers compared to boys. It was also evident that children were more likely to take up work responsibilities with or without studying as they grow older. For instance, while 12-14-year-old children were highly unlikely to be inactive (2.31 percent), about 47.98 percent of them were full-time workers and a third of similar children combined work and study.

Table 1. Childhood work and schooling circumstances by age cohort, birth order, and gender

Work and school combinations		*Gender group*		*Age cohort (years)*			*Birth order*		
	Pooled	Boys	Girls	4-8	9-11	12-14	First	Second	Later
Work-only	43.47	42.03	44.92	41.16	43.45	47.98	47.33	42.05	39.2
School-only	10.90	12.41	9.39	8.04	14.29	13.87	11.74	14.36	6.82
Combining both	22.81	23.80	21.83	7.72	38.69	35.84	31.32	24.1	9.09
Inactive	22.81	21.77	23.86	43.09	3.57	2.31	9.61	19.49	44.89

Note: *Values are the proportion of children in each child group.*

As one may also expect, inactivity and work-only conditions dominate at early childhood ages (4-8-year-old), perhaps either due to the inability to handle many of the tasks at this age and exempted from working but also those children younger than seven were not expected to be in the school. It is also found that most of the children who combined work and study were mainly either from 9-11-years-old or older ones. Generally speaking, the results showed that while work-only was the main activity for children in all age groups but slightly rising as we go up, combining work and study seems to be the daily task for most middle and older age children. Childhood work also shows similar patterns by childbirth order as in the age-cohort.

Looking at the main activities of children at specific ages, excluding inactive children, Figure 1 shows that after the age of nine, children tend to combine work and study while the odds of being a fulltime worker declines though it remains higher. After the age of 13, again the proportion of full-time working children increased, perhaps due to dropping-out from school after finishing lower primary school while the proportions of children who combined work and study and school-study declined. Moreover, showing a steep decline, it shows that inactive children in the early their ages were more likely to join one of the other groups after turning seven, resulting in the rise of the odds of being in all other groups. Similar age and work associations have been reported by Tafere & Pankhurst (2015) in Ethiopia; Singh &

Khan (2016) in India; Bhalotra & Heady (2003) in Ghana; Khanam (2008) in Bangladesh; and Grootaert (1999) in Cote-d'Ivoire, although none of the studies investigated the long-term school progression.

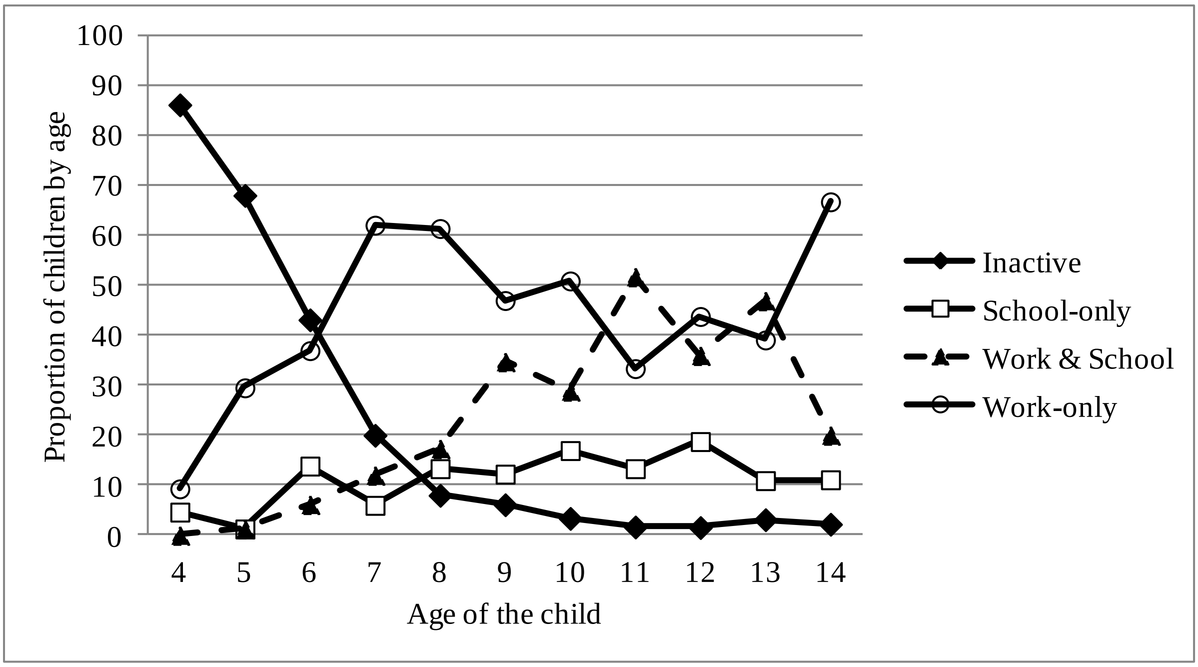

Figure 1. The distribution of children by age based on work and school combinations

4.2 Understanding the long-term migration patterns and characteristics

Households in general, and individuals, in particular, participate in various migration types: rural to rural, rural to urban, and in some cases in cross-border migrations. The discussions on migrations in this paper focus on village out-migrations, either to other rural village or urban areas. Rural out-migration, involving relatively many people, often the youth, is critical to understand the mobility of active farm labor force, to design appropriate human capital and labor market policies, and to envisage the role of the migrant labor force in the development and structural transformation process. By non-migrants, we refer individuals who have not left the baseline village, even if they left the baseline households and formed their own families within the same village. As pointed out in the background section, internal rural out-migration could be driven by variables related to the migrant, households, and residence villages. Below we discussed some the key factors in relation to long-term migration statuses.

Table 2 presents migration characteristics of children disaggregated by sex and birth order. We find statistically significant associations between these child-related factors and the decision to out-migrate or remain in the baseline villages. Village out-migration was generally dominated by females; almost twice as many females left the villages compared to males.

Table 2. Migration characteristics of children by gender and siblings' birth order

Migration characteristics	Sex (N=764)* All sample children Pooled	Male	Female	*t*-Test by gender	Birth order (N=720) First born	Second born	Later-born
Out-migrated, all migrants (N=764)	35.08	25.58	44.83	5.68***	29.01	33.75	36.36
Out-migrated and tracked (N=652)	24.08	15.34	33.55	5.55***	17.86	24.29	24.71

*Note: the value excludes children who died after the baseline survey.

Results show that about 44.83 percent and 33.55 percent of all females were migrants when considering all and tracked out-migrant females, respectively. On the contrary, 25.58 percent of males were migrated regardless of tracking status and that those tracked males constitute about 15.34 percent of all resurveyed males.

Village out-migration relatively increases with the birth order; later born children were more likely to leave the villages and also constituted higher proportion among the resurveyed targets. The results indicate that 36.36 percent of the third or later born children were migrants and also constituted about 24.71 percent of tracked later-born targets. Several factors may lead to a relatively higher tendency of migration among this group of children. For instance, resources competition leading to difficulties in access to farmland through inheritances or via traditional land arrangements, in one hand, as push factors but also having better access to childhood education in the other may have contributed for their outmigration.

With regard to migration destinations, Table 3, other districts, mainly nearby urban areas were most important destinations for about 43.31 percent of resurveyed children. From a gender perspective, it shows that other rural or urban districts in the respective regions were also the main destinations for more than 40 percent of males and females alike. In this regard, we found that neighboring urban districts to the survey villages such as Debre Birhan town for Kormargefia and Milki (both from Debre Birhan villages); Lalibela, Woldia, Kombolcha, and Dessie towns for Shumsha; Haramaya and Awoday towns for Adele keke, and Dilla town for Adado were the major nearby urban destinations. Moreover, children also migrated to other regions such as from Adado to Oromia region around Shakiso, Kibre Mengist, and Adola to work in gold mining areas; from Adele keke to Harar and Dire Dawa cities mainly for business and through marriage; and from Dinki village to Argoba and Dulecha districts in Afar region. We also noted that females also migrate to other rural villages or towns mainly through marriage. Moreover, unlike males, females also tend to migrate to Addis Ababa and abroad mainly to Arab countries including Saudi Arabia, Lebanon, and United Arab Emirates.

Migration destinations based on birth order also showed a similar pattern as gender. Based on the birth order, while other districts in each region were major destinations for all migrants, many second-born children also left to Addis Ababa while a substantial proportion of other children also went to other rural villages or nearby towns within the baseline districts. In this regard, the systems theories of migration argue that migration patterns could be guided by the dynamic links between migration origin and destination area contexts (Bakewell 2014). For instance, we saw the role of collective behavior of return migrants in Adado village through providing information to villagers regarding the nature of work at destination – Shakiso gold mining area, and the returns leading to a continuous flow of migrants from Adado to this area.

Table 3. Migration destination by gender and siblings' birth order among tracked children

	Gender group			Siblings' birth order		
Migration destinations	All surviving children			First-	Second-	Later-
Tracked only (N=157) (%)	Pooled	Male	Female	born	born	born
Another village or town in a district	20.38	17.31	21.90	22.78	13.04	25.00
Another district in a region	43.31	44.23	42.86	48.10	36.96	40.63
Another region	14.01	17.31	12.38	13.92	13.04	15.63
Addis Ababa	22.29	21.15	22.86	15.19	36.96	18.75
Total number of tracked /resurveyed migrants	157	52	105	79	46	32

In line with the birth order and migration associations, our descriptive analyses also revealed that about half of all out-migrations occurred during the ages of 20-24 years; with the average of 21 years at the time of the first village outmigration.

We also looked at the main reasons for village outmigration decisions and presented in Table 4. It is showed that a combined three-quarter of all the migrations was made due to marriage and to seek for gainful employment or to work. Gender-disaggregated results further showed that while about 65.38 percent of males (28.57 percent for females) migrated to work or searching for jobs, almost half of migrant females (23.08 percent for males) left the villages to other rural or urban areas through marriage or forming new families. For males, migration through marriage may mean that after marriage they could move to have a better access to farmland, to start non-farm jobs or rarely migrated to live near the bride's family. The gender-specific insights were contextually sensible and theoretically plausible in that females are more likely to follow their spouses in rural Ethiopia than to out-migrate for work purposes.

Twice as many of resurveyed females as males tend to out-migrate for schooling. Similarly, schooling and related issues were the main reasons for one in every four resurveyed children who migrated before turning twenty. Unlike the results from focus group discussions in each community, the individual level analyses did not reveal farmland shortage as the main driver of long-term out-migration decision.

Table 4. Reasons for rural out-migration among tracked resurveying targets, 2015/16

Reasons for migration for tracked RTs	Group by gender (%)			Age (years) at first migration (%)		
	Pooled	Males	Females	Under 20	20-24	Above 24
To work or looking for job	40.76	65.38	28.57	42.22	37.80	46.67
Marriage or divorce	39.49	23.08	47.62	33.33	42.68	40.00
Schooling and others	19.75	11.54	23.81	24.44	19.51	13.33
Number of RTs in the group	157	52	105	45	82	30

However, agricultural land shortage in the villages could be one of the underlying factors for the above reasons. The land shortage may play an important role among married targets and we cannot rule out its potential effects on marriage decisions. The results also indicate that while the odds of job-oriented out-migration increased with age, but RTs who migrated at or after the age of 20 would equally likely to out-migrate for marriage and related reasons.

Table 5 reports the associations between mutually exclusive combinations of work and school activities and children's migration profiles when adults. Results show that while the relative ratio of schoolchildren increased among migrant individuals, we note a significant reduction of inactive children and slightly among full-time childhood workers in migration.

Table 5**.** Migration statuses based on childhood work and school conditions for all children

Childhood work and schooling characteristics, *proportions*	Pooled sample	Non-migrants (A)	All Migrants (B)	*t*-Tests (A) & (B)
School-only	10.9(0.01)	10.3(0.01)	13.1(0.02)	-1.15
Combining both	22.8(0.01)	20.2(0.02)	29.1(0.03)	-2.80***
Work-only	43.5(0.02)	44.4(0.02)	40.7(0.03)	0.98
Inactive	22.8(0.01)	25.2(0.02)	17.2(0.02)	2.55**

Note: Values in the parentheses are standard errors. The values indicate childhood work characteristics of migrant and non-migrant individuals. Our test results show that 41.1 percent of schoolchildren at baseline out-migrated which was significantly higher (P<1%) compared to the migration rate among non-schoolchildren at baseline, 29.8 percent. However, we did not find a significant difference in terms of the hours worked between migrant and non-migrant targets.

Mean test results show that the reduction in the proportion of full-time childhood workers in migrant and non-migrant children was statistically insignificant. That is, work-only children still make up larger part among migrants. On the other hand, while those who combined work and study were highly likely to migrate; inactive children tend to stay in the villages.

To recap, the migration patterns based on childhood characteristics showed that migrant and non-migrant children were different by gender, birth order, and some childhood-work conditions. Accordingly, migrants were more likely to be females, later-born siblings, and schoolchildren with or without working. Previous studies also conclude that youth and better-educated individuals dominate labor migration in developing economies. In these countries, males dominate work related labor migrations. Moreover, the fact that rural out-migration was dominated by schoolchildren suggests that human capital formation and higher expected income might have also driven the decision to out-migrate; hence migration decision is less likely to be a random decision.

Household characteristics and children's adulthood migration status

Hypothetically, migrants should come mainly from large household sizes where labor can be easily released with minimal strain on farming and other labor-intensive activities, from affluent households who can bear the monetary cost associated with migration, but also from those households who face stringent farmland shortages. However, the results revealed that looking at children based on households' wealth, children from all wealth groups were equally likely to out-migrate (Table 6). We note that while the proportion of children from poorer (second quintile) households increased by about 6 percentage points among migrants (although statistically insignificant), other children show slight reductions (except children from the fifth quintile) among migrant children.

Theoretically, the new economics of labor migration theory (Stark & Bloom 1985; Stark & Levhari 1982; Stark & Lucas 1988; Stark & Taylor 1991), assuming households as migration decision makers, explains migration as a strategy to reduce income risk and diversify income sources where credit and insurance markets are imperfect and inexistent. In this regard, many migrant children could have been from lower wealth quintile households where stayers reduce income shocks and smooth their consumption through remittances. Also informed by the community level findings, lack of farmland and thin local labor market could have also pushed the youth from the poorest households. In contrast, due to better childhood education opportunity and the ability to finance migration expenses, children from affluent households may have also migrated perhaps driven by different purposes compared to the former. However, despite such potential differences in terms of the drivers of migration, we noted that regardless of wealth statuses children were equally likely to out-migrate.

Table 6. Household characteristics of the migrant children

	The proportion of migrants		
Household characteristics(N=764)	No	Yes	Mean test (*t*-values)
Child is from the poorest households	35.47(0.02)	33.33(0.04)	0.48
Child is from poorer households	33.97(0.02)	40.14(0.04)	-1.37
Child is from middle households	35.71(0.02)	32.43(0.04)	0.75
Child is from richer households	35.68(0.02)	32.93(0.04)	0.66
Child is from the richest households	34.57(0.02)	36.84(0.04)	-0.55
Adult member left or died since 1997	32.89(0.02)	42.85(0.04)	-2.39**
HH accessed land via redistribution	29.02(0.02)	43.49(0.03)	-4.04***
Soil fertility decreased	32.7(0.02)	37.0(0.03)	-1.26
Expects diminishing size of land	36.6(0.02)	30.5(0.03)	1.52
Household took credit since 1997	39.6(0.02)	30.3(0.03)	2.69***
Head had physical health problem	32.2(0.02)	43.2(0.03)	-2.32**
Household size (number) in 1999	7.38(0.11)	7.41(0.15)	-0.15

Note: *For all binary variables, yes=1 and no=0. Values in the parentheses are standard errors. The values show the proportion of migrants from the respective household specific variables. The last column tests the mean or proportions of migration between the two variable responses. The poorest households are those from the first quintile and the richest households are from the fifth quintile in the wealth quintile distribution.*

With regard to historical migration experiences in the households or death of an adult household member since 1997, children from such households were also 10 percentage points more likely to leave the villages, i.e. children from these households were significantly more likely to migration compared to those who are not from such households. The other major family backgrounds that are associated with migration status included whether the household accessed farmland through government land redistribution in the village, if the household took any loans as small as 20 Birr in the two years prior to the baseline survey, and head’s physical health conditions. In general, our findings show that children from households who accessed farmland through redistribution, took loans in the last two years, and heads with some kind of physical health problems were highly likely to have out-migrated in the last sixteen years compared to their peers in the comparison households.

4.3 Empirical results

4.3.1 Diagnosing the covariate balancing

Covariate balancing is one of the diagnostic procedures providing a useful indicator whether the weighting strategy through propensity scores created plausible counterfactuals. As pointed out earlier we measured childhood work in two ways: (1) using mutually exclusive childhood work and school combinations and (2) childhood work index. In the first approach, school-only children constitute the control group (involving no work), while the treated are those who combined work and study and full-time workers. In the second approach, the control children are those who have non-positive work index and the rest were grouped into three levels of treatment – lower, moderate, and high work intensities.

A covariate is said to be balanced when its distribution is similar across all treatment levels. In non-experimental data, covariates can be made balanced by weighting strategy since treatment assignment and outcomes are related to the covariates. Rubin (2001) presents diagnostics to assess the standardized difference in the means of the scores between the treatment groups, the ratio of the variances of the propensity scores in the two groups, and, for each covariate, the ratio of the variance of the residuals orthogonal to the propensity score in the two groups. The standardized differences in means should generally be less than 0.25, and the variance ratios should be close to 1 or generally between 0.5 and 2 (Rubin 2001).

The results presented using Appendix 1 show that of all 18 covariates, except 3 covariates for multi-task children and 2 covariates for work-only children, the standardized differences are all less than 0.25 and mostly close to zero. On the other hand, while all variance ratios are between Rubin's acceptable ranges, 10 variables both for multitasking and work-only children are close to one. Graphical diagnostics also suggest that the control children are identical to the treatment children on the observables thus their long-term migration decision is conditionally independent of these observables. We also presented similar numerical diagnostics when childhood work is measured using indices (Appendix 1b). While all the standardized differences of all covariates are close to zero for moderate-intensity childhood workers, all covariates except one for low-intensity working children and seven for high-intensity childhood workers are close to zero. For the latter, the maximum standardized difference was 0.49 for sex of the baseline household head. On the other hand, the variance ratios show that while covariates for treatment levels are between 0.6 and 1.3, except children from the poorer wealth quintile and with high- intensity of childhood work which is 0.49.

4.3.2 Checking for overlap

When the overlap assumption is met each child could get any treatment levels with similar probability. Rubin (2001) proposed a set of criteria based on comparing the distribution of the propensity score between treated and untreated subjects in a sample to determine whether regression adjustment adequately eliminate bias when comparing outcomes between treatment groups. Some authors propose that comparison of baseline covariates may be complemented by comparing the distribution of the estimated propensity score between treated and untreated subjects in the matched sample (Ho et al. 2007). In our multi-valued treatment, the overlap assumption is satisfied when there is equal chance of observing each child across all levels of treatment (childhood work conditions). Unlike binary treatments, we scrutinized the overlap graphs displaying the estimated density of the predicted probabilities that a non-working child is a non-working child and the estimated density of the predicted probabilities that a working child is a non-working child.

The GPS plots show that a school-only child (control) is equally likely to combine its study with work and be fulltime childhood laborer. Moreover, subsequent graphical analyses also show no evidence of the violation of the overlap assumption. In none of the graphs, the estimated GPS density distributions have too much mass around zero or one. Similarly, we also examined the GPS density distributions for treatment based on the intensity of childhood work index. The GPS plots indicate that non-working (non-positive work indices) children have similar odds of being observed across low, moderate, and high intensities of childhood work, suggesting for no evidence that the overlap assumption is violated. However, we find that in terms of achieving overlap between control and multi-level treated children, the combinations of work and school seems to perform better than the index approach.

4.3.3 Childhood work - school combinations and long-term migration

We estimate the long-term effects of childhood work on migration decisions using various combinations of work and study as multi-valued treatments and childhood work index. The treatment and outcome models are estimated in the same framework using IPWRA and the auxiliary equations in the treatment effects estimation procedure are presented in Table 7.

***Treatment model covariates*:** The treatment models, columns 7 & 8, are estimated using multinomial logit regression model using school-only children as a control group. The control children were studying-only at baseline while multitasking and work-only children engaged in work in different extents. We controlled for child-related, family-background, and village-specific covariates in the treatment models. The treatment models are identical and common in the ATE and ATET estimations; the only changes are in their outcome equations.

Among child specific controls, results showed that the child age has been statistically significant in the multi-task children's treatment equations. The estimates indicate that for every one year increase in child's age, the relative risk of combining work with study relative to school-only condition would increase by about 1.3 times (exponentiated value). Moreover, unlike child-specific covariates, many of the household level and head related variables significantly explain the likelihood of children's work and school participation. The results indicate that while an increase in the proportion of children in the household equality likely to reduce the probability of combining work and study and full-time childhood laborer, children from households where any adult household member left or died in the previous two years or works in off-farm activities increased the relative risk of children to combine their work with study. Furthermore, we also find that children with heads who are not satisfied with the quality of education at schools have a higher relative probability to be multitasking or work-only children in various works compared to the odds of being a school-only child.

Household wealth also explains some of the variations in the treatment levels. Using children from the poorest households as a reference group, children from poorer and wealthier households were less likely to combine work and study or exclusively work compared to be school-only children. In other words, when we go from children in the poorest households to those in better-off households, they seemed to specialize in schooling instead of combining work with school and work-only compared to their peers from the poorest households. The results provide some insights that the combinations of work and study among children may also be the reflections of parent wealth status. In this regard, for those who engaged in work to meet household economic needs, childhood work could be eased when parent get wealthier.

Outcome model covariates**:** outcome equations are the second part of the estimations. The outcome estimators are produced using logit model, the migration status of the child after the baseline survey. We have three migration outcome equations based on the treatment levels. Controlling for relevant observables, the estimations are conducted for the full sample of children. Unlike the treatment models, the outcome (migration) equations differ across the two treatment effects: ATE and ATET (see the table description for detail).

Looking at the critical covariates in ATE and ATET treatments, we find that long-term village out-migration decisions for children across different treatment levels (work conditions in relation to schooling) are associated with sex of the child and partly with birth order; age, sex, and literacy status of the head; participation of an adult household member in off-farm economic activities at baseline, out-migration or death of an adult member in the two years prior to the baseline survey, decline in soil fertility, whether the household grew a new crop variety in the last seven years, and household wealth status. Among several key variables to explain long-term migration decisions by treatment levels, we find that multitasking and fulltime childhood working males have 44.6 percent and 35.3 percent (exponentiated values), respectively, times less odds of migration probability compared to the odds for females in the respective groups. Moreover, using children from the poorest households in the respective treatment levels, while wealth status doesn't play a significant role in migration decision among work-only children, school-only and multitasking children from better-off households have by far the several times more odds of migration.

Moreover, results also suggest that long-term out-migration significantly increases (decreases) with village distance from the nearest main town among work-only (multitasking) children compared to schooling-only children. Besides, migration among multitasking children showed significant and positive associations with the presence of productive safety net program in the village and whether the local agro-ecology is *Dega* (3000m above Sea level) or *Weina Dega* (1500-3000m above Sea level) and the seasonal average village farm wage rate during baseline survey. Intriguingly, village-related factors weakly associated with long-term migration decisions among schooling-only children. To recapitulate, the results suggest that several factors at various levels interplayed to shape children's long-term migration decision based on childhood conditions. Since we have achieved balance in most of these covariates and created comparable children with equal probability of being in the alternative treatment groups, the treatment effects on the outcome are less likely to be driven by these variations.

Table 7. The long-term effects of work and school combinations on migration decisions – Auxiliary equations for IPWRA estimations for ATE and ATET

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Outcome (Migration) Equations			*Outcome (Migration) Equations*			*Treatment (work) Equations*	
Covariates	School-only	Multi-task	Work-only	School-only	Multi-task	Work-only	Multi-task	Work-only
Child is male	-0.393	-0.807*	-1.041***	0.732	-0.820**	-0.657*	-0.315	-0.412
	(0.979)	(0.457)	(0.269)	(1.301)	(0.404)	(0.364)	(0.299)	(0.270)
Age of the child							0.233***	-0.0182
							(0.0767)	(0.0701)
Child birth-order								
2nd born child vs. eldest	-0.385	-0.438	-0.00186	-0.941	-0.186	-0.310	0.629	0.352
	(0.761)	(0.477)	(0.345)	(1.150)	(0.451)	(0.458)	(0.399)	(0.358)
Youngest vs. eldest	-0.412	0.442	-0.649	-1.211	1.233*	-1.067**	0.697	0.777
	(0.919)	(0.889)	(0.416)	(1.198)	(0.732)	(0.530)	(0.649)	(0.563)
Age of the head in 1999	-0.0354	-0.00449	0.0265**	-0.175**	-0.0127	0.0402**	0.00826	0.0196
	(0.0434)	(0.0219)	(0.0124)	(0.0686)	(0.0208)	(0.0185)	(0.0154)	(0.0137)
Head is male	-7.546***	-0.134	-0.0237	-8.472***	-0.299	0.369	-0.123	-0.125
	(2.397)	(0.637)	(0.405)	(1.955)	(0.651)	(0.583)	(0.473)	(0.438)
Head is literate	-1.158	-0.0611	0.212	-4.319***	-0.388	0.571	0.198	-0.442
	(0.865)	(0.474)	(0.334)	(1.553)	(0.440)	(0.465)	(0.358)	(0.325)
Head satisfied with Educ. quality							0.274	-0.744*
							(0.446)	(0.380)
Household size in 1999	-0.101	-0.0678	0.0841	-0.200	-0.0800	0.0748	-0.0855	0.0195
	(0.308)	(0.122)	(0.0768)	(0.446)	(0.105)	(0.115)	(0.0753)	(0.0674)
Proportion of children in the HH	-2.468	2.266	1.415	-3.714	3.141*	2.479	-3.979***	-3.910***
	(4.749)	(1.857)	(1.303)	(7.040)	(1.753)	(1.701)	(1.524)	(1.439)
A member work in off-farm jobs	2.035**	1.445**	-0.0496	3.641**	0.791	-0.0788	0.858**	0.515
	(0.874)	(0.617)	(0.335)	(1.661)	(0.535)	(0.453)	(0.427)	(0.396)
Adult HH member left since 1997	1.871	-0.0564	0.697*	4.632**	-0.0190	0.999*	1.079**	0.591

	(1.260)	(0.457)	(0.368)	(1.981)	(0.433)	(0.511)	(0.430)	(0.420)
Head expects decline in land size	-0.257	-0.823*	-0.339	0.814	-0.709	-0.777*	1.143***	0.998***
	(1.203)	(0.496)	(0.328)	(1.650)	(0.431)	(0.429)	(0.393)	(0.363)
Soil fertility declined	2.048**	0.378	-0.154	3.390***	0.347	0.0856	-0.267	0.455
	(0.858)	(0.620)	(0.336)	(1.046)	(0.500)	(0.428)	(0.341)	(0.322)
HH grew a new crop since 1992	3.873***	-0.395	0.373	6.254**	0.246	0.596	0.479	-0.0103
	(1.368)	(0.492)	(0.397)	(2.430)	(0.471)	(0.481)	(0.412)	(0.404)
HH used same land size since 1994	-0.0615	-0.142	0.0414	1.962*	-0.320	0.164		
	(0.776)	(0.470)	(0.388)	(1.172)	(0.435)	(0.513)		
HH wealth quintiles								
Poorer vs. Poorest	3.772	2.141***	-0.395	4.577	1.959***	-0.723	-2.029***	-1.959***
	(2.294)	(0.702)	(0.502)	(3.234)	(0.705)	(0.752)	(0.625)	(0.579)
Middle vs. Poorest	4.460*	1.393	0.285	8.260***	1.595**	0.852	-1.818***	-1.712***
	(2.281)	(0.864)	(0.487)	(2.976)	(0.790)	(0.570)	(0.624)	(0.581)
Richer vs. Poorest	3.110*	3.056***	-0.256	5.757***	2.881***	-0.0353	-1.350**	-1.794***
	(1.588)	(0.879)	(0.489)	(1.869)	(0.848)	(0.639)	(0.663)	(0.612)
Richest vs. Poorest	4.461**	2.770***	-0.0797	8.449***	2.517***	0.0414	-1.421**	-2.476***
	(2.199)	(0.928)	(0.528)	(2.682)	(0.936)	(0.672)	(0.650)	(0.614)
Distance of the village	0.324	-0.377***	0.131**	0.407	-0.188	0.171**	-0.0154	-0.0105
	(0.264)	(0.125)	(0.0591)	(0.333)	(0.126)	(0.0759)	(0.0674)	(0.0575)
Village has no PSNP	1.722	4.209***	0.583	5.092**	3.401***	0.308	0.338	-0.520
	(1.473)	(0.960)	(0.373)	(2.018)	(0.881)	(0.505)	(0.407)	(0.361)
Avg. farm real wage rate	-0.836	1.098***	-0.0658	-0.644	0.830***	-0.277	0.200	-0.266*
	(0.510)	(0.304)	(0.160)	(0.490)	(0.293)	(0.198)	(0.162)	(0.151)
Constant	3.761	-6.115***	-4.180**	3.163	-5.865**	-5.478***	-0.256	5.639***
	(3.681)	(2.201)	(1.710)	(6.141)	(2.323)	(2.089)	(1.728)	(1.619)

*Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Columns (1) – (3) are the outcome equations for the ATE and under columns (4) – (6) are outcome equations for the ATET. Both estimations share identical treatment equations, columns (7) & (8). The treatment effects estimations were done on 572 observations using IPW regression adjustment method. The outcomes are modeled using logit model while the treatment models are multinomial logit.*

The findings contribute to the long-established discussion regarding the drivers of labor out-migration. Unlike other empirical studies that assume homogeneous childhood conditions among individuals and try to explain their decision to migrate, we provide evidence that child, household, and village related factors play differential roles on long-term migration decisions based on childhood conditions. It also implies that rural-urban wage differential in a dual economy (Lewis 1954) alone may not drive rural-urban labor migration. Childhood work and schooling could affect long-term migration decision through their effects on the human capital formation and children's future employability in the non-farm economic sectors.

Treatment effects estimation

In addition to identifying the drivers of long-term migration decisions based on childhood work conditions, our main objective is also to estimate the causal effects of being a multi-tasking child relative to school-only and working-only child relative to school-only on their respective long-term migration decisions.

The average treatment effect (ATE) suggests that the likelihood of migration among work-only children could be about 12.9 percent less than the potential outcome (POM) of 44.8 percent which would have been observed had they exclusively studied (Table 8). The effect is statistically significant. However, the ATE does not show evidence that going from school-only to multitasking significantly affects the odds of long-term out-migration, meaning that schoolchildren despite their childhood work conditions are equally likely to out-migrate.

Table 8. The average treatment effects of childhood work on migration decisions

Childhood work conditions	*β*	*Robust SE*	*z*	*P*	*[95% Conf. Interval]*	
(Combining both)	-0.0461	0.0552	-0.84	0.404	-0.1542	0.0621
(Work-only)	-0.129**	0.0506	-2.55	0.011	-0.2280	-0.0298
POM for Control (School-only)	0.448***	0.0433	10.33	0.000	0.3627	0.5325

Note: Significance levels- *** P<0.01, ** P<0.05

Furthermore, we also estimated the average treatment effects on the treated (ATET**)** to understand to what extent the likelihood of migration would change for working-children along different levels of treatment (Table 9). Using children who combined work and study as controls, the probability of long-term migration among full-time working children would be about 8 percent less ($P \leq 0.1$) than the counterfactual of 40 percent, which could have occurred if fulltime working children had studied while working.

Table 9. Average Treatment Effects on the Treated (ATET) among childhood workers

	ATET for work-only children			*ATET for multitasking children*		
Childhood work conditions	*β*	*Robust SE*	*z*	*β*	*Robust SE*	*z*
(School-only)	0.0496	0.0673	0.74	0.1480***	0.0554	2.67
(Work-only)	-0.0811*	0.0493	-1.64	***Control group***		
(Combining both)	***Control group***			0.0980**	0.0498	1.97
POM estimates	0.4000***	0.0425	9.40	0.3206***	0.0358	8.96

Note: Significance levels- *** *P*<0.01, ** *P*<0.05, * *P*<0.1

The findings in Table 9 also show that using work-only children as controls, both school-only and multitasking children were 14.8 percent and 9.8 percent, respectively, more likely to migrate in the long-term compared to the counterfactual level of migration which is estimated to be 32 percent if they had been full-time workers. However, the last estimation might have been driven by child education which is common across treatment and not for the control. This is harmoniousness with the concept that investment in human capital is as important as the process of migration (Sjaastad 1962). In other words, despite large rural-urban or farm and non-farm wage gaps, we might observe fewer migrants, perhaps due to the requirements of some forms of human capital. In addition to the role of adult human capital on migration, we argue that village out-migration decision could also be a form of long-term decision getting its basis quite at earlier child's age through participation in childhood work and schooling.

The results, in general, show that there is strong evidence that work-only children were more likely to stay in the villages compared to their peers who attended schooling and similar on observable factors. This, in turn, implies that work-only children are more likely to continue working in subsistence farming when adults. On the other hand, schoolchildren are more likely to leave the villages and take up non-farm jobs in other areas. This evidence reaffirms the lively debate that educated youth are leaving the agriculture sector and the rural areas. When the rural labor market is imperfect and fails to absorb the fast-growing rural youth population, migration could be the next option for schoolchildren when grown up.

What is the association between various childhood work and school combinations and the reasons and destinations of migration among migrants? We estimated logit regression for reasons for migrations and migration destinations (Table 10). Results show that compared to work-only children, children who combined work and study were more likely to migrate for economic reasons, i.e. looking for a job or to work while no significant difference is found among school-only relative to work-only peers. But, schoolchildren and full-time childhood workers were equally likely to migrate due to marriage and related social issues later in life.

Results associated with migration destinations show that the differences in childhood work and school conditions were not sustained by differences in the migration destinations. This shows that once children decide to out-migrate (crossing the hurdle – the decision to migrate); they would likely to migrate to similar destinations regardless of childhood work differentials. Perhaps, location advantages in one hand the origin and destination area contexts in other could have dictated the migration destinations in the villages. For instance, we noted that most children from Adado migrated to the gold mining area in Adola. But, this doesn't necessarily mean that they also work in similar jobs at the destination areas.

Table 10. The associations between childhood work and migration reasons and destinations

	Migration reasons		*Migration destinations*		
	(1)	(2)	(3)	(4)	(5)
Covariates	Economic (job search)	Marriage -related	Within districts	Within regions	Other regions or abroad
Work-school combinations[a]					
School-only	-0.0358	-0.251	-0.453	0.0996	-0.0221
	(0.760)	(0.684)	(0.840)	(0.526)	(0.511)
Combining work and school	1.240*	-0.409	0.0566	0.0291	0.126
	(0.651)	(0.613)	(0.708)	(0.433)	(0.438)
Other covariates[1]					
Child-related controls	Yes	Yes	Yes	Yes	Yes
Household-related controls	Yes	Yes	Yes	Yes	Yes
Village-level factor controls	Yes	Yes	Yes	Yes	Yes
Observations	136	136	185	198	198

Note: Significance levels- P<0.1, [a]*Reference group: Work-only*

Moreover, assuming migration as a means of efficient allocation of resources, Sjaastad (1962) also argues that migration is a strategy through which individuals use their skills to get a better return in other areas, the decision being done after cost-benefit analyses and comparing future discounted earnings and current earnings. In this regard, those who combined work and study may have the skills advantage when adults to earn better income somewhere in non-

[1] *Child controls [sex and birth order interactions and age of the child], head and household controls [age, sex, and literacy status of the head, if the head satisfied with the quality of education, household size, proportion of children in the household, off-farm participation. adult migration or death, expectation on future land size, soil fertility, adoption of new crop verities, and wealth status in quintiles], village related controls [distance from the nearest town, real wage rate, having PSNP and local agro-ecology]*

farm economic activities leading to higher probability of economic migration. It also indicates that migration is selective in terms of human capital: skills, knowledge, and experiences.

To sum up, the results thus far suggest that using how children used to combine work and study; we found significant effects of childhood work on children's long-term migration decisions**.** Moreover, the results show that multi-task children were more likely to migrate for economic reasons compared to their peers who were exclusively working.

4. 3.4 Childhood Work Index (CWI)

While combinations of childhood work and school could be one of the options to measure childhood work, it does not show the intensities of children's work, for instance, among those who combined work and study. As an alternative strategy, using 17 childhood work indicator variables, we constructed a childhood index addressing this limitation. We included almost all commonly used child labor variables in farming communities including work and study combinations and also some other proxies which indicate potential child labor use in a typical rural household. While it needs further examination not only from its empirical convenience viewpoints but also from policy dimension, we find that it is a more stable indicator than other proxy variables which could be prone to measurement errors and recall biases.

After constructing the index, we categorized children into four treatment groups or levels. Those with zero and negative indices were used as controls; non-working children while those who have positive CWI were assigned into three equal size treatment groups: low, moderate, and high work intensities (Figure 2).

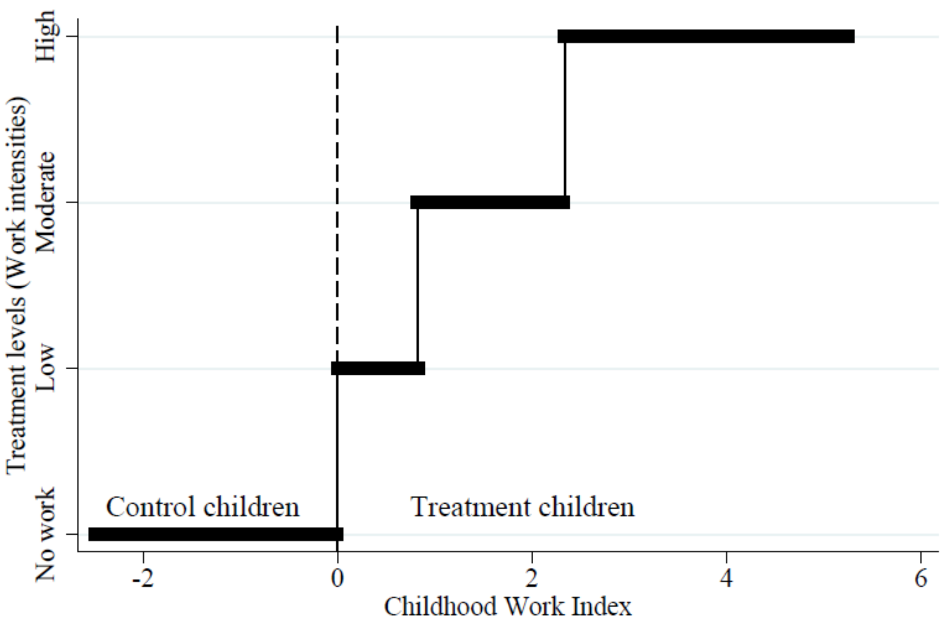

Figure 2. Child groups into control and treatment categories using work indices

In the end, we used 447 children (56.65 percent) as controls and 114 children (14.45 percent) in each of the three treatment levels. Accordingly, we used these groups to denote multiple treatment levels and conducted similar causal analysis using IPWRA method to identify how working at one of the treatment levels could affect long-term migration decision relative to non-working (control) children.

Controlling similar covariates we used in the previous IPWRA models and including age-adjusted grade attainment, results showed that when we go from none-working to high-intensity workers, the probability of long-term outmigration reduced by about 13.34 percent (Table 11) compared to the average of 33.56 percent which would have been observed if they were non-working children. However, we didn't find significant differences among children working at low to moderate intensities compared to the control children. This reaffirms the previous conclusion that work-only children were more likely to stay in the villages.

Table 11. Average treatment effects (ATE) of childhood work on long-term migration

Childhood work index	*β*	*SE*	*z*	*P-value*	*[95% Conf. Interval]*	
(Low vs. No work)	0.0922	0.0606	1.52	0.128	-0.0266	0.21107
(Moderate vs. No work)	0.0388	0.0505	0.77	0.443	-0.06029	0.137841
(High vs. No work)	-0.1334***	0.0328	-4.07	0.000	-0.19771	-0.06916
POM for No work	0.3356***	0.0232	14.49	0.000	0.29018	0.38093

Note: ****P*<0.01

A simple cross-tabulation also reveals that about 81 percent of the high-intensity working children were identified as work-only children based on how they combined work and study. Furthermore, about 92 percent of school-only children were classified as non-working children based on the index, implying substantial level of overlap between the two childhood work measurement strategies in identifying working and non-working children.

Results on the effects of childhood work among those who actually worked at low, moderate and high-intensities (ATET) are reported using Table 12. Using low-intensity working children as controls, the probability of long-term migration could have been about 16.30 percent less among moderately-working children than the average of 52.41 percent which would have been observed had they had worked at low intensity. Furthermore, using the same control children, the average migration for high-intensity working children would have been 17.65 percent less than the counterfactual value of 41.95 percent had they engaged in low-intensity work. The ATET estimations using children at low intensity of childhood work as a control group further revealed that as we go from low to high levels of childhood work intensity, the likelihood of outmigration on average declines.

Table 12. The average treatment effects of childhood work among childhood laborers

	ATET for Moderate work intensity			*ATET for High work intensity*		
Childhood Work Index	*β*	*SE*	*z*	*β*	*SE*	*z*
(No work vs. Low)	-0.2198***	0.0671	-3.27	-0.1405**	0.0646	-2.18
(Moderate vs. Low)	-0.1630**	0.0733	-2.22	-0.0015	0.0960	-0.02
(High vs. Low)	-0.2263***	0.0712	-3.18	-0.1765***	0.0643	-2.75
POM for Low	0.5241***	0.0605	8.66	0.4195***	0.0508	8.26

Note: ***P<0.01; **P<0.05

5. Caveats of the study

Selection bias is the main identification problem in work and school participation during childhood and also in migration when adults. The study has some caveats worth mentioning. First, although we attained a balance between children on observables, there could be some unobserved factors such as innate abilities which may interplay with the error terms. Besides, the selective decisions of parents to assign children to work and study based on their expected returns might also affect the reliability of our estimates. Both selection problems may result in estimation biases. The study doesn't account for biases arising from such unobserved effects. Second, in the childhood work-school combinations, we had little information on how multi-task children actually allocated their time between work and study. Due to lack of data on the specific time utilization for the competing activities, we couldn't identify trade-offs and reflect on the optimal combinations level. Finally, while we utilized the pooled data to conduct the IPWRA analyses, detailed evidence could have been presented if disaggregated analyses were conducted by sex of the child, childhood work types, parent wealth status, and location. However, due to small sub-samples to draw control groups, we did not explore that.

6. Concluding remarks

The paper investigated the long-term effects of childhood work and schooling conditions on children's migration decisions and patterns. We used a novel prospective panel dataset from rural Ethiopia generated through a follow-up individual-level tracking survey of 4-14-year-old children at baseline (1999/2000) after sixteen years in 2015/2016. The data were analyzed using inverse-probability weighted regression adjustment, a doubly robust estimation method. We find that village out-migration in general was dominated by females and schoolchildren.

Our treatment effects model shows that full-time childhood work may trap children in the villages later in life compared to schoolchildren. This, in turn, implies that full-time childhood workers are more likely to continue farming when adults. On the other hand, schoolchildren are more likely to leave the villages and take up non-farm jobs in other areas. Controlling for observables, we also find that children who combined work with schooling were highly likely to out-migrate from the villages due to economic reasons. We argue that this could be perhaps that the condition may have given multi-tasking children the opportunity to acquire relevant work skills and build their entrepreneurial spirit leading to out-migrate and work in non-farm activities. This study presented new evidence in the related literature that childhood conditions in a fast-changing developing economy context may affect children's long-term migration behavior. Consequently, the implicit assumption of homogeneity in childhood conditions while studying adulthood migration decisions need to be revisited.

The findings imply that investment in child schooling might be as relevant as enabling the youth to out-migrate from the rural areas. Therefore, investment in rural education should also be accompanied by supportive and expansionary labor market policies in the rural areas to absorb the youth or in the urban areas to avoid non-gainful rural-urban migration.

Appendices

Appendix 1. Covariate balancing for childhood work and school combinations; Control group: *School-only children and* Treatment variable: *Childhood work and school combinations*

	Standardized diff.		*Variance ratio*		*Standardized diff.*		*Variance ratio*	
	Raw	*Weighted*	*Raw*	*Weighted*	*Raw*	*Weighted*	*Raw*	*Weighted*
	Combining work and school				Work-only			
Age of the child	0.4429	0.1553	0.6123	0.6910	-0.1398	0.0873	1.1746	1.2058
Child is male	-0.1173	0.0694	1.0212	1.0020	-0.1882	0.0843	1.0217	1.0010
Birth order[1]								
2nd eldest	0.0403	-0.2775	1.0244	0.8271	0.0000	-0.2049	0.9906	0.8837
3rd eldest	-0.2121	0.0694	0.6654	1.0950	0.1123	-0.0228	1.1511	0.9681
Age of the head	0.2088	0.0502	0.7858	0.9586	0.2247	0.0527	0.9639	1.1024
Head is male	-0.1534	0.1418	1.3418	0.7695	-0.0982	0.0953	1.2134	0.8458
Head is literate	-0.0400	0.0370	0.9977	1.0091	-0.2577	0.0390	0.9635	1.0094
Education quality	0.0971	0.2931	0.8260	0.7308	-0.2890	0.2080	1.4322	0.8190
Household size	-0.1392	0.0629	1.7142	1.5606	-0.0042	0.0617	1.6939	1.4318
Prop. Of children	-0.2075	-0.0508	0.8979	0.9736	-0.2211	-0.1131	1.0490	1.0959
Off-farm participation	0.3496	-0.0567	1.2841	0.9745	0.1388	-0.1286	1.1351	0.9332
Adult left or died	0.4154	-0.4242	1.8725	0.6588	0.2191	-0.3635	1.4827	0.7191
Farm size declines	0.3559	-0.0476	1.6250	0.9566	0.2940	-0.0759	1.5269	0.9288
Soil fertility declines	0.2119	-0.2977	0.9595	1.1603	0.1311	-0.2803	0.9800	1.1560
Grew new crop variety	0.3262	-0.1398	1.4818	0.8709	0.0163	-0.1843	1.0182	0.8243
Wealth quintiles								
Poorer[2]	-0.1270	0.0546	0.8090	1.1031	-0.1363	0.0519	0.7931	1.0979
Middle	-0.1750	0.1030	0.7373	1.2090	0.0226	0.1476	1.0220	1.2970
Richer	-0.0352	-0.1762	0.9401	0.8213	0.0905	-0.1867	1.1212	0.8094
Richest	-0.0740	-0.0541	0.9336	0.9400	-0.2780	-0.0377	0.7309	0.9586
Village distance	0.0846	0.0839	0.8314	1.2180	0.0435	0.0539	1.2272	1.1697
Real farm wage rate	0.4758	-0.1152	1.2695	0.8903	0.0766	-0.1329	0.7681	0.7979
No PSNP	-0.1801	-0.0335	1.0440	1.0033	-0.0761	0.0348	1.0199	0.9950

Reference groups: [1,2]Firstborn and Children from the poorest households, respectively

Appendix 2. Covariate balancing for childhood work index;
Control group: *No-work (Non-positive work index) and* Treatment variable: *Childhood work index*

	Standardized diff.		*Variance ratio*		*Standardized diff.*		*Variance ratio*		*Standardized diff.*		*Variance ratio*	
	Raw	*Weighted*	*Raw*	*Weighted*	*Raw*	*Weighted*	*Raw*	*Weighted*	*Raw*	*Weighted*	*Raw*	*Weighted*
	Low intensity				*Middle intensity*				*High intensity*			
Age of the child	0.4947	-0.2465	0.9063	0.9139	0.5966	0.0547	0.8771	0.8909	0.4822	-0.0314	0.7658	0.6615
Child is male	0.1832	0.0382	1.0109	1.0023	0.2605	0.1287	0.9873	0.9967	0.2525	-0.3029	0.9900	0.8834
Birth order (ref.:1st born)												
2nd eldest	0.1592	0.0074	1.1499	1.0067	0.1032	0.2375	1.1021	1.1673	0.1688	-0.2447	1.1523	0.7369
3rd eldest	-0.5769	0.1672	0.5210	1.1305	-0.3887	-0.1781	0.7105	0.8137	-0.6130	0.0083	0.4821	1.0074
Child education (ref: no grade)												
Grade 1	-0.0172	-0.1838	0.9672	0.5880	0.1161	0.1274	1.3061	1.3032	-0.0848	0.0312	0.7973	1.0733
Grade 2	0.0971	-0.0262	1.3083	0.9257	0.2870	-0.0215	1.9053	0.9394	-0.2560	-0.0657	0.3441	0.8171
Grade 3 and above	0.2097	-0.1060	1.6674	0.6914	0.0182	-0.0009	1.0609	0.9978	-0.2560	-0.0798	0.3441	0.7645
Age of the head	-0.0588	-0.0735	1.0001	1.1089	0.0928	-0.0751	0.9570	1.2667	0.0979	0.0085	0.8549	0.6943
Head is male	-0.5321	0.0745	2.6534	0.8475	-0.1443	0.0656	1.4614	0.8662	-0.3232	-0.4905	2.0434	1.8594
Head is literate	-0.0420	-0.1173	1.0114	0.9716	-0.1216	-0.1332	0.9991	0.9662	-0.2657	-0.1250	0.9528	0.9686
Education quality	0.0765	-0.3067	0.9250	1.2497	0.1960	-0.0645	0.7763	1.0680	-0.0506	0.0043	1.0588	0.9949
Household size	-0.3273	-0.0401	0.9219	0.7984	-0.3220	-0.0704	0.6529	0.7491	-0.4175	0.2480	0.7961	1.1198
Prop. Of children	0.1325	0.0679	0.9235	0.9350	0.0555	0.0525	1.0178	1.1337	-0.0543	0.0382	1.0269	0.8314
Off-farm participation	-0.0492	0.1414	0.9673	1.1188	-0.0875	0.2294	0.9275	1.1734	0.0602	0.0943	1.0543	1.0831
Adult left or died	0.3437	-0.0576	1.5200	0.9075	0.1345	0.1051	1.2286	1.1617	0.0010	-0.0969	1.0087	0.8436
Farm size declines	0.1811	-0.1920	1.1759	0.7845	-0.0387	-0.0024	0.9647	0.9980	-0.1445	0.2924	0.8404	1.2137
Soil fertility declines	0.6091	0.0015	0.9373	0.9999	0.5269	0.0759	0.9825	0.9914	0.9441	-0.1190	0.6719	0.9907
Grew new crop variety	0.0774	-0.1878	1.1412	0.7469	0.3024	0.0089	1.4655	1.0117	0.2046	0.0854	1.3345	1.1028
Wealth status (ref: poorest)												
Poorer	-0.2519	0.1125	0.6535	1.1966	-0.4681	0.1572	0.3492	1.2718	-0.1956	-0.2904	0.7327	0.4888
Middle	-0.0006	0.0862	1.0097	1.1116	0.0316	-0.0347	1.0592	0.9530	0.2755	-0.1523	1.4177	0.7847
Richer	0.1980	-0.0490	1.3062	0.9304	0.1465	0.0204	1.2301	1.0286	0.2975	-0.0076	1.4224	0.9890
Richest	0.1716	-0.0172	1.2207	0.9789	0.2663	-0.0415	1.3075	0.9489	-0.1898	0.3918	0.7384	1.3347
Village distance	0.0975	0.2299	1.3124	1.3566	0.0414	0.1542	1.5505	1.1687	0.3588	-0.3590	1.2603	1.5459
Real farm wage rate	0.4298	0.0423	0.9404	0.6254	0.4566	0.0922	0.9667	0.8618	0.6087	0.1790	1.0058	0.5078
No PSNP	-0.2352	-0.1715	1.1170	1.0245	-0.3660	-0.1093	1.1205	1.0230	-0.3375	-0.3291	1.1221	0.9949

References

Abegaz, B. (1999). *Aid and reform in Ethiopia* (Working Paper No. 35725). Washington, DC.: The World Bank.

Atnafu, A., Oucho, L., & Zeitlyn, B. (2014). *Poverty, youth and rural-urban migration in Ethiopia* (Working Paper 17). Migrating out of Poverty RPC. United Kingdom: University of Sussex.

Bakewell, O. (2014). 'Relaunching migration systems', *Migration Studies*, 2/3: 300–18.

Berhanu, B., & White, M. (2000). 'War, Famine, and Female Migration in Ethiopia, 1960–1989', *Economic Development and Cultural Change*, 49/1: 91–113. DOI: 10.1086/452492

Bezu, S., & Holden, S. (2014). 'Are rural youth in ethiopia abandoning agriculture?', *World Development*, 64: 259–72. Elsevier Ltd. DOI: 10.1016/j.worlddev.2014.06.013

Bhalotra, S., & Heady, C. (2003). 'Child Farm Labor: The Wealth Paradox', *The World Bank Economic Review*, 17/2: 197–227.

Bigsten, A., Isaksson, A., Söderbom, M., Collier, P., Zeufack, A., Dercon, S., Fafchamps, M., et al. (2000). 'Rates of Return on Physical and Human Capital in Africa's Manufacturing Sector', *Economic Development and Cultural Change*, 48/4: 801–27.

Blunch, N.-H., & Laderchi, C. R. (2015). 'The winner takes it all: Internal migration, education and wages in Ethiopia', *Migration Studies*, 3/3: 417–37. DOI: 10.1093/migration/mnv008

de Brauw, A. (2015). 'Migration, Youth, and Agricultural Productivity in Ethiopia'. *Immigration, agricultural employment, and trade: International perspectives*. Presented at the Annual Meeting of the Allied Social Science Association (ASSA), Boston, Massachusetts. Milwaukee, WI, USA: Agricultural and Applied Economics Association (AAEA).

de Brauw, A., & Mueller, V. (2012). 'Do Limitations in Land Rights Transferability Influence Mobility Rates in Ethiopia?', *Journal of African Economies*, 21/4: 548–79.

de Brauw, A., Mueller, V., & Woldehanna, T. (2013). 'Motives to Remit: Evidence from Tracked Internal Migrants in Ethiopia', *World Development*, 50: 13–23.

CSA. (2002). 'Ethiopia - Child Labour Survey 2001-2002 (1994 E.C) (Statistical Bulletin No. 262)'. Addis Ababa, Ethiopia: Central Statistical Agency.

Deshingkar, P., & Grimm, S. (2004). 'Voluntary Internal Migration: An Update'. Overseas Development Institute.

Ezra, M., & Kiros, G.-E. (2001). 'Rural out-migration in the drought prone areas of Ethiopia: a multilevel analysis', *International Migration Review*, 35/3: 749–71.

FDRE. (2003). 'Rural Development Policy and Strategies'. Addis Ababa, Ethiopia: Government of the Federal Democratic Republic of Ethiopia, Ministry of Finance and Economic Development.

Gebru, G. W., & Beyene, F. (2012). 'Causes and consequences of out-migration on rural households ' livelihood in Gulomekeda district , Tigray , Ethiopia', *Agricultural Research and Reviews*, 1/1: 26–33.

Gibson, M. A., & Gurmu, E. (2012). 'Rural to Urban Migration Is an Unforeseen Impact of Development Intervention in Ethiopia', *PLoS ONE*, 7/11: 1–8. DOI: 10.1371/journal.pone.0048708

Gray, C., & Mueller, V. (2012). 'Drought and Population Mobility in Rural Ethiopia', *World Development*, 40/1: 134–45.

Grootaert, C. (1999). *Child Labor in Côte d'Ivoire: Incidence and Determinants*. Policy Research Working Papers. The World Bank. DOI: 10.1596/1813-9450-1905

Hailemariam, A., & Adugna, A. (2011). 'Migration and Urbanization in Ethiopia: Addressing the Spatial Imbalance'. Hailemariam A. & Teller C. (eds) *The Demographic Transition and Development in Africa*, pp. 145–65. Springer Netherlands: Dordrecht.

Ho, D. E., Imai, K., King, G., & Stuart, E. A. (2007). 'Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference', *Political Analysis*, 15/3: 199–236. DOI: 10.1093/pan/mpl013

Imbens, G. W. (2000). 'The Role of the Propensity Score in Estimating Dose-Response Functions', *Biometrika*, 87/3: 706–10.

Imbens, G. W., & Wooldridge, J. M. (2009). 'Recent Developments in the Econometrics of Program Evaluation', *Journal of Economic Literature*, 47/1: 5–86.

IMF. (1999). 'Ethiopia: Recent economic developments'. Washington D.C.: International Monetary Fund.

Kassa, B. (2004). 'Resettlement of peasants in Ethiopia', *Journal of Rural Development*, 27/Winter: 223–54.

Kassie, G. W., & Aye, G. (2017). 'The Nexus between livelihood diversification and farmland management strategies in rural Ethiopia', *Cogent Economics & Finance*, 5/1: 1275087. Cogent. DOI: 10.1080/23322039.2016.1275087

Khanam, R. (2008). 'Child labour and school attendance: evidence from Bangladesh', *International Journal of Social Economics*, 35/1/2: 77–98.

Kloos, H., & Aynalem, A. (1989). 'Settler migration during the 1984/85 resettlement programme in Ethiopia', *GeoJournal*, 19/2: 113–27. DOI: 10.1007/BF00174641

Kuffa, G. (2014). *Population Stabilization Report, Ethiopia*. Addis Ababa, Ethiopia.: Ministry of Health.

Lechner, M. (2001). 'Identification and estimation of causal effects of multiple treatments under the conditional independence assumption'. Lechner M. & Pfeiffer F. (eds) *Econometric Evaluation of Labour Market Policies*, Vol. 13. ZEW Economic Studies (Publication Series of the Centre for European Economic Research (ZEW), Mannheim, Germany): Physica, Heidelberg.

Lewis, W. A. (1954). 'Economic Development with Unlimited Supplies of Labour', *The Manchester School*, 22/2: 139–91.

Linden, A., Uysal, S. D., Ryan, A., & Adams, J. L. (2016). 'Estimating causal effects for multivalued treatments: a comparison of approaches', *Statistics in Medicine*, 35/4: 534–52.

Mberu, B. U. (2006). 'Internal migration and household living conditions in Ethiopia', *Demographic Research*, 14: 509–40.

MoE. (2002). 'Education Statistics Annual Abstract 1994 EC (2001–02'. Addis Ababa, Ethiopia: FDRE Ministry of Education.

Morrissey, J. (2008). 'Rural-urban migration in Ethiopia', *Forced Migration Review: Climate change and displacement*, 31: 28–9.

Murendo, C., Keil, A., & Zeller, M. (2011). 'Drought impacts and related risk management by smallholder farmers in developing countries: evidence from Awash River Basin, Ethiopia', *Risk Management*, 13/4: 247–63.

National Planning Commission. (2016). 'Growth and Transformation Plan II (GTP II) (2015/16-2019/20), Volume I: Main Text'. Federal Democratic Republic of Ethiopia, Addis Ababa.

Rahmato, D. (2004). 'Searching for tenure security?: the land system and new policy initiatives in Ethiopia'. Addis Ababa, Ethiopia.: Forum for Social Studies.

Rosenbaum, P. R., & Rubin, D. B. (1983). 'The central role of the propensity score in observational studies for causal effects', *Biometrika*, 70/1: 41–55. DOI: 10.2307/2335942

Rubin, D. B. (1974). 'Estimating causal effects of treatments in randomized and non-randomized studies', *Journal of Educational Psychology*, 66: 688–701.
——. (2001). 'Using propensity scores to help design observational studies: application to the tobacco litigation', *Health Services and Outcomes Research Methodology*, 2/3: 169–88.
Singh, R., & Khan, S. in. (2016). *Perspectives on children's work and schooling: Evidence from a longitudinal study in Andhra Pradesh and Telangana, India* (ILO Asia- Pacific Working Paper Series). ILO DWT for South Asia and Country Office for India - New Delhi: International Labour Organization.
Sjaastad, L. A. . (1962). 'The Costs and Returns of Human Migration', *Journal of Political Economy*, 70/5: 80–93.
Stark, O., & Bloom, D. E. (1985). 'The New Economics of Labor Migration', *The American Economic Review*, 75/2: Papers and Proceedings of the Ninety-Seventh Annua.
Stark, O., & Levhari, D. (1982). 'On migration and risk in LDCs', *Economic development and cultural change*, 31/1: 191–96.
Stark, O., & Lucas, R. E. B. (1988). 'Migration, Remittances, and the Family', *Economic Development and Cultural Change*, 36/3: 465–81.
Stark, O., & Taylor, J. E. (1991). 'Migration Incentives, Migration Types: The Role of Relative Deprivation', *The Economic Journal*, 101/408: 1163–78.
Tadele, F., Pankhurst, A., Bevan, P., & Lavers, T. (2006). 'Migration and Rural-Urban Linkages in Ethiopia: Cases studies of five rural and two urban sites in Addis Ababa, Amhara, Oromia and SNNP Regions and Implications for Policy and Development Practice (Research Group on Wellbeing in Developing Countries Ethio'. ESRC WeD Research Programme.
Tafere, Y., & Pankhurst, A. (2015). *Can Children in Ethiopian Communities Combine Schooling with Work*. Working Paper 141, Oxford: Young Lives.
Tegegne, A. D., & Penker, M. (2016). 'Determinants of rural out-migration in Ethiopia: Who stays and who goes?', *Demographic Research*, 35/1: 1011–44. DOI: 10.4054/DemRes.2016.35.34
Teklu, T. (2003). *Rural lands and evolving tenure arrangements in Ethiopia: Issues, evidence and policies* (FSS Discussion Paper No. 10). Addis Ababa, Ethiopia.: Forum for Social Studies.
TGE. (1993). 'The National Population Policy of Ethiopia'. Addis Ababa, Ethiopia: Transitional Government of Ethiopia (TGE).
Todaro, M. (1997). 'Urbanization, Unemployment, and Migration in Africa: Theory and Policy'. *Reviewing Social and Econimic Progres in Africa*. New York, Population Council.
Uysal, S. D. (2013). 'Doubly Robust Estimation of Causal Effects with Multivalued Treatments'. Institute for Advanced Studies, Vienna.
Webb, P., & von Braun, J. (1994). *Famine and Food Security in Ethiopia: Lessons for Africa*. Washington, D.C: International Food Policy Research Institute (IFPRI).
World Bank. (2009). *Abolishing School Fees in Africa: Lessons Learned in Ethiopia, Ghana, Kenya and Mozambique.* (E. F. Birger & D. Craissati, Ed.). The World Bank.
——. (2016a). 'Ethiopia: Priorities for Ending Extreme Poverty and Promoting Shared Prosperity: Systematic Country Diagnostic (Federal Democratic Republic of Ethiopia No. 100592–ET)'. The World Bank.
——. (2016b). 'Ethiopia's Great Run: The Growth Acceleration and How to Pace It'. The World Bank.