Does labor mobility positively impact rural transformation? Insights from a decade-long longitudinal study

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Abstract

Some countries still limit internal mobility with strict household registration requirements that curb rural-urban migration. Policymakers argue that easing these restrictions could, among other concerns, harm the rural economy and threaten national food security by reducing agricultural labor, though global evidence on this is mixed. This paper adds to the scant evidence on this issue in Sub-Saharan Africa by examining the impact of labor mobility on Ethiopia's rural economy using 10 years of Ethiopian Socioeconomic Panel (ESPS) data and nonparametric preprocessing matching techniques for parametric causal inference. The study reveals that during both pre- and post-government change periods, migrant-sending households increased their family labor supply by 104 and 167 days and cultivated more land per person-increased by 26% and 29%, respectively. Also, the proportion of households participating in the local land rental-market increased by 6 percentage points in both eras, in a market where only about 30% participate. Migrant-sending households saw an increase in output per worker by 56% and 29% during the respective periods. Efficiency gains and remittance led to positive welfare gain for households. These findings highlight the role of labor migration in reducing poverty and transforming the rural economy by decreasing disguised unemployment, raising subsistence wages, and improving land-use efficiency.

Keywords: Rural-urban migration Rural factor markets Agriculture WelfareStructural transformation Impact evaluation Ethiopia .

1 Introduction

In many developing countries, including Ethiopia, rural-urban migration is often viewed as disrupting the rural labor market because it reallocates labor away from agriculture toward manufacturing and services while hurting the former. The key concern here is that rural-urban migration presents a loss of human capital for migrant-sending rural areas, leaving subsistence agriculture, dominated by smallholder farmers, short of labor and thereby undermining food production and food security. Also, as rural-urban migration parallels a low level of industrialization in these countries, most urban economies could experience high unemployment and poverty due to the inflow of new labor force [1]. This perspective, however, overlooks the potential for rural-urban migration to improve rural livelihoods through remittances, risk diversification, and more efficient allocation of labor and land [2].

Empirical evidence on the impacts of rural-urban migration on the rural economy remains mixed. Some studies find limited or negative effects on agricultural production. For example, Akram et al. [3] report no intra-household labor substitution, i.e., no increase in workdays on a farm among migrant households in Bangladesh, while Quisumbing and Mcniven [4] find no effect of migration on agriculture production in the Philippines. Evidence from China similarly suggests that village-level migration does not significantly affect household labor supply [5]. In contrast, data from the Chinese Health and Nutrition Survey showed that Women left at home do more farm work, which would not have been the case if the migration never happened in the household [6].

This study is a comprehensive exploration that provides new empirical evidence to better understand the impact of labor mobility on the border rural economy transformation by studying households' participation in origin communities factor markets pre- and post-migration using the ten-year-long Ethiopian Socioeconomic Panel Survey (ESPS) data and applying a nonrandomized impact analysis method, i.e., nonparametric preprocessing matching techniques for parametric outcome analyses[1]. The longevity of the panel data offers the opportunity to study how a change in economic development model following the change in government in Ethiopia in 2018 influences the impact of rural-urban migration on rural labor supply, land use, and agriculture outcomes.

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2 Country Context

Ethiopia has a history of being reluctant to encourage labor mobility and instead places burdensome administrative procedures. For example, local administrators are unwilling to provide official letters to those intending to move out. The letter indicates their credentials and place of origin. It is crucial for migrants to freely move where better economic opportunities are and get identification cards ($Kebele$ IDs) from their destination areas [7]. Ethiopia is in the company of many countries where policymakers have long feared taking measures to accelerate rural-urban migration and are apprehensive of adverse migration outcomes in rural areas, hence put restrictions instead.

Ethiopia has a relatively fast-growing population and economy. The rural population is expected to continue to grow for years to come, as rural-to-urban migration does not offset the increases in rural people. The rural population increased by 24.4 percent between 2013 and 2021, while rural-to-urban migration remained 2 percent over time. The expanding rural population puts pressure on agricultural land, the average land size per household has declined from 1.25 ha in 2006 to 0.89 ha in 2020 [8]. The smallholder farming system often makes the rural labor markets thin. Hence, in recent years, the lack of economic opportunity in rural areas has driven the rise of economic inactivity, it increased from 21 percent in 2019 to 26 percent in 2022, while it decreased from 26 percent to 21 percent in urban areas during the same period [9].

The present study aims to revisit whether migration out of the rural labor market could be understood as a key component of the rural development process. It explains how labor mobility facilitates rural economic transformation in Ethiopia. Also, since 2018, the country has shifted from the renowned 'Development State' economic development ideology to a new Home-Grown Economic Reform Agenda (HGERA), aiming to shift the development paradigm from a state to private sector-led development. In this regard, the study attempts to understand if the story of the interaction between labor mobility and rural transformation is consistent regardless of the government ideology and ideological change in public policy.

3 Methodology

Let the linear form of a household labor supply with migration and without migration for a household i be presented as:

$$y_i = \gamma_i + \beta_{ij} \sum_{n=1}^{n} X_{ij} + \theta_i D_i + u_i \tag{1}$$

where, y_i is the household labor supply of household i, X is a multi- dimensional vector of observed characteristics of the household, where $J = 1, ..., N$ denotes different socio-economic and community related characteristics of the household, respectively, and D_i is a dummy variable equal to 1 if the household has a memebr who migrated (migrant household) and 0 otherwise. Let y_2 represents the average value of household labor supply for the migrant household and y_1 represents the average value of household labor supply for the non-migrant household. Based on the framework of potential outcomes approach of Roy [10] and Rubin [11], the average impact of migration on migrant households, i.e. the average treatment effect on the treated (ATT), will be,

$$ATT = \mathrm{E}(Y_2 - Y_1 | D = 1) \tag{2}$$

The value $E(Y_1|D = 1)$, the average household labor supply for migrant households would have registered in absence of migration, is not observed (is the missing data). However, we have the value $E(Y_1|D = 0)$, and if we consider Y_1 as a comparison outcome for Y_2 and measure the difference in the average household labor supply between the two groups, we will have,

$$\Delta = \mathrm{E}(Y_2|D = 1) - E(Y_1|D = 0) \tag{3}$$

There is a mathematical difference between equation 2 and equation 3, and adding and subtracting the value $E(Y_1|D = 1)$ in equation 3 results as follows:

$$\Delta = \mathrm{E}(Y_2|D = 1) - E(Y_1|D = 1) + E(Y_1|D = 1) - E(Y_1|D = 0) \tag{4}$$

$$\Delta = \ ATT + E(Y_1|D = 1) - E(Y_1|D = 0) \tag{5}$$

$$\Delta = \ ATT + SB \tag{6}$$

where, SB is a difference between the average household labor supply for the migrant households that would have been registered in the absence of migration and the observed average household labor supply for non-migrant households. It captures the extent of selection bias. This implies that a simple mean household labor supply difference between the migrant and non-migrant households will not necessarily measure the accurate impact of migration unless and otherwise

SB is equal to zero. Thus, to undertake a sound impact analysis, we apply a nonparametric way to condition on X_j, which is the Propensity Score Matching (PSM) method that enables us to construct a counterfactual group statistically similar to the migrant household (treated group) from the pool of non-migrant households (untreated group) data.

To minimize bias, related with model selection, and reduce the preprocessing data inefficiency, we employ a method that reduces model dependence via preprocessing data with semi-parametric and non-parametric matching estimation method [12]. First, we estimate a logit model of migration on various baseline socio-demographic, economic, and community characteristics of the household.

$$D_i = f(X_i) \tag{7}$$

where, D_i is a dummy variable that equals 1 for migrant households and 0 otherwise, X_i is a vector of observable baseline factors of household i. Second, we apply a nonparametric matching strategy involving a Nearest Neighbor matching estimator with replacement among propensity scores. Applying an appropriate threshold on the maximum propensity score distance (caliper) is vital for producing good matching. Hence, the preprocessing applies calipers of width equal 0.2 of the standard deviation of the logistic distribution, aiming to match more similar households and reduce bias in turn. Also, we use radius matching as it uses as many comparison cases as are available within the caliper but not those that are poor matches.

Third, we conduct the outcome analysis using the matched sample in a quite robust way. In the parametric analysis, we first fit a weighted linear least square regression (LLS), to the counterfactual group only (weighted logistic regression for dichotomous outcome variables).

$$y_i = f(X_i) \tag{8}$$

where, y_i is an outcome variable for household i and X is multi-dimensional vector of observed characteristics for household i from non-migrant group. Once the coefficients are estimated from the counterfactual group, we impute the missing outcome $E(Y_1|D = 1)$ through simulation using weighted regression. The ATT is then be obtained by $E(Y_2|D = 1) - E(\hat{Y}_1|D = 1)$. Given the matching strategy that is based on matching with replacement and radius matching, we found it important to incorporate weights in the analysis that reflect the number of non-migrant households that were used as a match. Consequently, the weights created by the preprocessing procedure estimate the ATT, with the non-migrant households weighted to be like the migrant households.

4 Data

The study uses the ten-year-long Ethiopian Socioeconomic Panel Survey (ESPS), a panel household data collection program conducted by the Ethiopian government in collaboration with the World Bank Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA). ESPS is a multitopic longitudinal survey representing regions and urban and rural areas. This report utilizes the rural datasets of the last five rounds of the ESPS– $ESPS_1$, $ESPS_2$, $ESPS_3$, $ESPS_4$, and $ESPS_5$, which we split into two unique two-panel datasets.

The study used data from rural households that participated in crop cultivation during the endline survey; as such, we created unique balanced panel datasets of 2,706 and 1,504 rural households for pre- and post-government change analysis, respectively. We conduct separate analyses using each unique, balanced panel dataset for the pre- and post-government change era.

The study draws on migration experience at the household level. For the pre-government change analysis, the study tracked households and their members from $ESPS_1$ to $ESPS_3$ and identified members who moved out to urban places during household visits in $ESPS_2$ and $ESPS_3$. Similarly, the study tracked households and their members from $ESPS_4$ and $ESPS_5$ and identified members who moved out to urban places during the household visit in $ESPS_5$. Households with members aged 10 or older who moved out are defined as migrant households. Self-reported rural-urban classifications often suffer from measurement bias, leading to misclassification of peri-urban areas as rural. Given this concern, we apply a motive-based, conservative reclassification of migration, focusing on economic and human capital factors such as employment, education, and household formation.

4.1 Baseline covariates conditioning households' migration decision and outcome variables

The empirical models discussed in Section 3 include pre-migration covariates that can affect the likelihood of migration and outcomes of interest to eliminate biases due to variable selection. Also, we refrained from controlling the participation model for unrelated pre-migration covariates. The procedure includes household demographics, human and social capital indicators, proxies for liquidity constraints, household productive capital, and proxies for localized drought events and economic activity. To ensure consistency, the study maintains a harmonized set of covariates across both the pre- and post-government change analyses; when exact indicators differ between the two panel datasets, the most proximate available proxies are utilized. Baseline pre-migration covariates are drawn from $ESPS_1$ data for the pre-government change analysis, and the $ESPS_4$ data for the post-government change analysis.

The study benefits from integrating alternative data sources with the survey data, such as Earth Observation (EO), to complement the model estimates and control for the contribution of complex socioeconomic and spatial conditions that are difficult to measure directly.

Temporal drought variability and local economic activity are controlled at village level (enumeration area (EA)). We calculate the Standardized Precipitation Evapotranspiration Index (SPEI). We use Night Time Light (NTL) radiance, the actual intensity of light emitted, as a proxy for measuring local economic activity and capturing infrastructure heterogeneity. Also, the empirical model incorporates administrative region fixed effects to control for spatial variation and heterogeneity across the study periods. To quantify SPEI and NTL at the EA level, we employ a geospatial buffer analysis. We use the geographic centroid of each EA, and delineate a 5 km radius circular buffer.

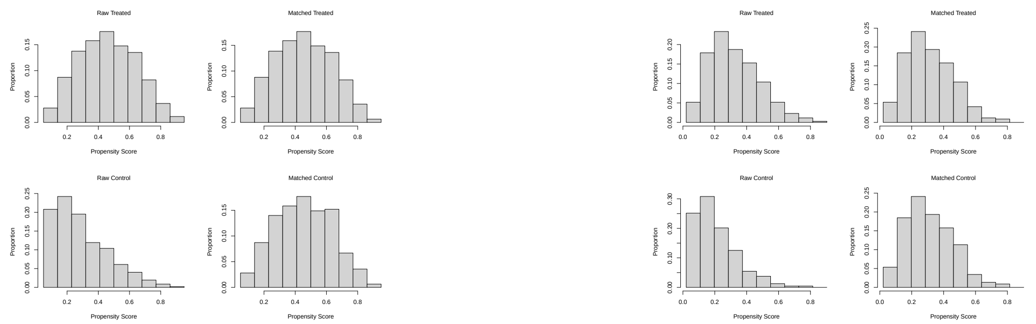
4.2 Outcome variables

The study aims to provide new empirical evidence to better understand the impact of labor mobility on the border rural economy transformation. As such, we classify the outcome into four categories: i) variables that explain households' interaction with the local land market, ii) variables that define the labor market outcome at household level, iii) variables that measure agriculture productivity, and iv) welfare of the households. The first category includes land utilization, measured by the size of cultivated land per capita. Participation in the rural land-renting market, measured by the likelihood of households engaging in renting-in or -out agricultural land transaction, is an additional outcome variable that refers to land efficiency use. Second, labor market outcomes are proxied by measuring the family labor supply, specifically the per capita number of days households spend on planting and harvesting activities. Third, we have an outcome variable to review the position of the households' productivity, proxied by the value of crop harvest per capita. Finally, we estimate households' welfare using the annual consumption expenditure. The outcome variables for the pre-government change analysis are estimated from the endline panel data of the first unique dataset, $ESPS_3$. Similarly, $ESPS_5$ is the endline survey for the second unique panel dataset and is used to estimate the outcome variables for the post-government change analysis.

5 Nonparametric Preprocessing and Balance Diagnostics

The primary purpose of matching is to break the actual relationship between D_i and X_i. We start estimating equation 7 using a logit regression and evaluate the level of balance of the groups and the balancing of each covariate. The preprocessing strategy discards 106 observations from the pre-government change analysis that fell outside of the common support region, and the matching estimation uses 2,283 and 1,464 observations for the pre-and post-government change analysis. For both scenarios, the nonparametric matching strategy involves a 'Nearest Neighbor' matching estimator with replacement among propensity scores within a preferred caliper of 0.05 and radius of 2. The preprocessing strategy ensures a tolerable overlap of the balance obtained from the logit estimation. The preprocessing, therefore, generates a total of 1,496 (710 Control and 786 Treated) and 741 (405 Control and 336 Treated) matched household datasets for the pre- and post-government change analyses, respectively for the parametric analysis and ATT estimation.

Figures 1 presents the pre-and post-government change analyses, respectively, present the distribution of the distance measure. It reaffirms that the original non-migrant household group can not serve as the comparable group for migrant households (see the leftmost side of the figures). After controlling for the imbalance, however, the propensity score distributions are statistically similar for both scenarios (see the rightmost panels of the figures), achieving the purpose of matching to break the link between migration and the premigration covariates.

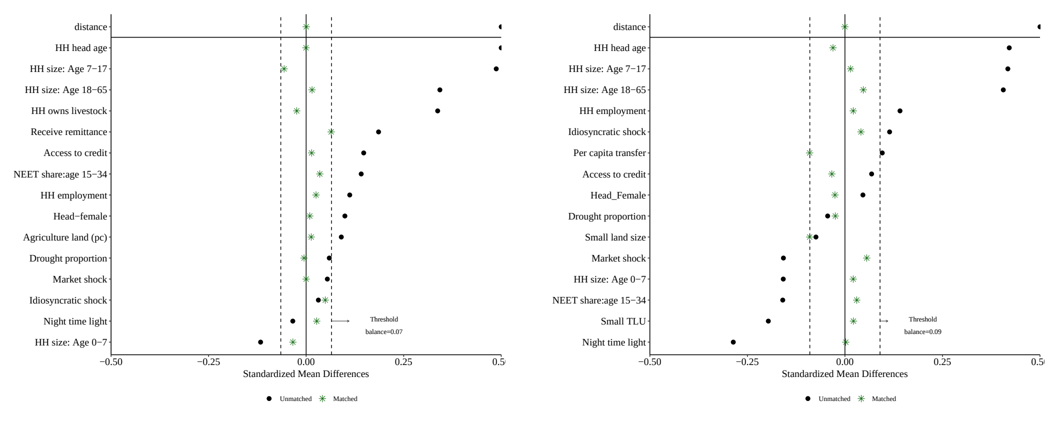


(a) Pre-government change analysis.

(b) Post-government change analysis.

Figure 1: Propensity score distribution in the original and matched groups.

We compute the difference in means of each covariate and divide by the standard deviation of the full migrant households' group. Rubin [11] recommended to have a standardized bias threshold of 0.25. Figures 2 shows standardized bias improvement after correcting imbalance. We set a threshold of 0.07 and 0.09 for the pre- and the post-government change analysis, respectively, and each covariate's standardized bias appeared to be below the threshold in both analyses. The results assure us that the matched datasets in both analyses produce a similar likelihood of sending out members to urban locations, i.e., $P(D_i = 1|X_{ij}) = P(D_i = 0|X_{ij})$.



(a) Pre-government change analysis.

(b) Post-government change analysis.

Figure 2: Standardized bias improvement after correcting imbalance.

We assess the absolute mean difference balance and the univariate balance distribution for each covariate, and both indicate that the preprocessing strategy reduces differences between groups in each covariate in both analyses. For the sake of space, we will present the result upon request.

Overall, the balance diagnostics indicate that the preprocessing strategy produces a good balance, sufficient to eliminate model dependence in the parametric analysis. Using matched datasets allows us to accurately measure the impact of D_i on Y_i, with low bias and variance.

6 Results

Table 1 and 2 present the estimates of ATT of each outcome variable for each analysis scenario.

Table 1: ATT conditioned on migration: pre-government change analysis

	ATT	Standard Errors	95% Confidence Interval
Cultivated land (Ha/pc)	0.06^{**}	0.0076	$(0.042; 0.072)$
Land rental-market participation (pp)	5.75^{**}	0.0224	$(0.013; 0.101)$
Family labor supply (days/pc)	104^{**}	23.7375	$(57; 151)$
Value of crop harvest (pc)	$1,212^{**}$	224	$(769; 1,652)$
Welfare (Consumption pae)	734^{**}	183	$(375; 1,102)$

$^{**}p < 0.05$

Note: Ha, pc, pae, pp refer to hectares, per capita, per adult equivalent, and percentage point, respectively. The value of crop harvest and consumption is in Ethiopian Birr. Land rental-market participation refers to the likelihood of participating in renting-in and -out of agricultural land.

Table 2: ATT conditioned on migration: post-government change analysis

	ATT	Standard Errors	95% Confidence Interval
Cultivated land (Ha pc)	0.05^{**}	0.0105	$(0.026; 0.067)$
Land rental-market participation (pp)	5.93^{**}	0.0265	$(0.006; 0.110)$
Family labor supply (days pc)	167^{**}	12.5210	$(142; 192)$
Value of crop harvest (pc)	$2,248^{**}$	908.9692	$(465; 4,044)$
Welfare (Consumption pae)	$4,597^{**}$	$1,143$	$(2,376; 6,869)$

$^{**}p < 0.05$

Note: Ha, pc, pae, pp refer to hectares, per capita, per adult equivalent, and percentage point, respectively. The value of crop harvest and consumption is in Ethiopian Birr. Land rental-market participation refers to the likelihood of participating in renting-in and -out of agricultural land.

The result indicates that rural-urban migration has a positive impact on labor intensity, agricultural output per capita, land rental markets, and welfare (measured by consumption per adult equivalent). This positive impact is observed regardless of government ideology or changes in public policy, though the magnitudes of the impact differ. The positive ATT value for cultivated land per capita reaffirms that the lost labor in rural areas does not leave the rural land uncultivated and hurt agriculture production. Instead, households with migration increased their family labor supply than it would be the case if the household is without migration by an equivalent of 104 and 167 days in pre- and post-government change periods, respectively. This implies that migration reduces disguised unemployment in rural areas. The reduction in surplus labor in rural areas is expected to facilitate the rise in labor productivity and output per worker; hence, we observe positive ATT for output per worker from the results in both scenarios, by about 1,212 Birr and 2,248 Birr in the pre-and post-government change periods, respectively. Also, the rising output per worker suggests that migration enables the remaining household members in migrant-origin households to adequately feed off their land. The results also attest that migration plays a role in creating an efficient rural land market. The share of households participating in the land rental-market is higher by 6 percentage points with migration than without during both pre- and post-government change era, signifying that migration improves the efficiency of the land markets, too. Estimated welfare gains are positive in both scenarios, as it is expected that remitance and efficiency benefits outweigh the production losses.

7 Conclusion

To summarize, our estimates highlight that labor mobility is linked to favorable changes to rural land and labor markets that facilitate rather than inhibit the transformation of the agriculture sector and the rural economy. The study evidently shows that the lost labor from migrant-sending rural areas, at least in recent times, appeared to be a catalyst for the rise in labor productivity and output per worker. In a country like Ethiopia, where land fragmentation became common due to an expanding rural population and economic inactivity is rising due to a lack of economic opportunities in rural areas, labor mobility helps to relieve this pressure by improving the efficiency of land markets as land rent-ins and rent-outs increase among migrant-sending households, and reducing disguised unemployment, resulting in increased output per worker and labor productivity in rural areas.

These results add to the emerging evidence that labor mobility can have positive effects on the rural economy beyond the remittance channel emphasized in much of the literature. Rather, the movement of people from rural to urban areas induces changes in factor market allocation that are catalytic to the rural economic transformation by increases rural labor productivity and efficiency of land use. In response to migration, households increase their family labor supply, which increases their output per worker, raising the rural subsistence wage. Those with more land than they can use, are more likely to rent the land out, putting land to its best use. This effect could be higher in the absence of frictions in the land market that Ethiopia has.

The findings have suggested that policy makers in countries like Ethiopia, should embrace rather than inhibit labor mobility as part of their economic transformation. They show that agriculture production is unlikely to suffer but could become more rewarding instead, given the increase in output per capita in-migrant origin households, which is instrumental for reducing poverty given rural households' reliance on agriculture and for generating a market surplus as well. With the right policies, land market transactions would increase, which adds the efficiency of land use. Thus, labor mobility is a base for not just poverty reduction, but for the broader economic transformation as well.

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