

The Winner Takes It All: Internal Migration, Human Capital and Wages in Ethiopia[†]

Niels-Hugo Blunch[‡]
Washington and Lee University & IZA
Lexington, VA 24450, USA
Email: blunchn@wlu.edu

Caterina Ruggeri Laderchi
World Bank
Washington, DC 20433, USA
Email: cruggeriladerchi@worldbank.org

JEL Classification: J240, J310, O150

Keywords: Internal migration, wages, human capital, Ethiopia

Abstract

Previous studies of migration have mainly examined international migration. Yet, internal migration is an important issue, especially in Sub-Saharan Africa. Using a recent nationally representative household survey, this paper examines internal migration in Ethiopia, focusing at the linkages among internal migration, human capital and wages. The results suggest that not only are migrants better educated and obtain higher wages than non-migrants, controlling for other factors (including human capital), they also obtain higher returns to their human capital. In other words, the more educated reap higher returns both from benefiting from migration and from higher returns to their human capital than non-migrants and from being better educated to begin with—that is, “the winner takes it all.” This result should be of concern to policy makers in Ethiopia, since individuals with low levels of human capital already is a vulnerable group, and the study therefore also discusses the policy implications of these results.

[†] This paper builds on a background paper commissioned by the World Bank’s Africa PREM Sector Department for the *Urban Labor Markets in Ethiopia: Challenges and Prospects* report. We thank Jeni Klugman for guidance and support. Remaining errors and omissions are our own. The views expressed here are those of the authors and should not be attributed to the World Bank or any of its member countries.

[‡] Corresponding author.

1. Introduction

While there arguably are many ways to improve one's livelihood, two stand out in particular. The first, and one of the most important ways of all, we argue, is through improving one's education. Alas, this has led to an entire field of study, namely that of human capital (Becker, 1964; Mincer, 1974). This literature generally finds that returns to education are substantial across countries, including Sub-Saharan Africa (Psacharopoulos, 1994; Psacharopoulos and Patrinos, 2004).

The second – and potentially more immediately rewarding – way is through changing one's economic conditions geographically through migration. The literature here has almost exclusively been focused at international migration that is, looking at how individuals who leave their country of origin – frequently to developed countries – fare in their “new” country, mostly in terms of employment and/or wages and incomes (Ajakaiye, Lucas and Karugia, 2006; Faini, de Melo and Zimmermann, 1999). Far less is known about internal migration within developing countries themselves.

This paper examines the returns to migration in Ethiopia, examining a recent nationally representative household survey. We explore four main research questions, namely (1) Is there a premium to migration? (2) Does the share of migrants in the current community matter? (3) Is the overall wage structure of migrants and non-migrants different? (4) Does the migration-wage association differ across educational attainment; in particular, are the returns to education the same for migrants and non-migrants? The combined results suggest that the more educated are the winners from increased migration, while the less educated are the losers. In other words, the more educated reap higher returns both from benefitting from migration and from being better educated to begin with—that is, “the winner takes it all.” This result should be of concern to policy makers in Ethiopia, since individuals with low levels of human capital already is a vulnerable group. Focus should therefore be shifted even more towards this group – for example in terms of skills upgrading and education – especially in areas with high levels of in-migration.

The remainder of this paper is structured as follows. The next section provides the institutional and historical background of migration in Ethiopia, while Section Three develops the conceptual and empirical framework. Section Four presents the data and descriptive analysis, while Section Five presents the results. Section Six concludes, discusses policy implications, and provides suggestions for further research.

2. Background: Migration in Ethiopia¹

While migration has been relatively low in Ethiopia by international standards, internal migration has always been one of the main vehicles for urbanization in Ethiopia—as it has been in other countries, also. In Ethiopia, as in other countries, there are many different possible reasons motivating migrants—typically grouped into “push” and “pull” factors, where the former denote characteristics in the destination area that are perceived as negative relative to other characteristics in the destination area that are perceived as negative relative to other (i.e., potential receiving) areas and the latter denote characteristics in the receiving area that are perceived as positive relative to the destination area.

Starting with the “push” factors, the combination of shortages of land, low agricultural productivity, and high population densities in northern Ethiopia and recurrent droughts throughout the country has been important historically, in turn leading to the creation of garrison towns in the south, southwest and eastern parts of Ethiopia as early as the early 1900s. This was reinforced with the establishment of Addis Ababa as the permanent capital, with the associated permanent need for labor and goods and services. This led to an improvement in infrastructure, including transportation—most notably the creation of the Djibouti-Addis Ababa railway. In turn, the construction of the railway helped contribute to the emergence of several towns along the route and along with them, also the emergence of financial and public services including banks, hospitals and schools. Urban infrastructure was further consolidated through the 1940s with the emergence of markets and the associated increased division of labor, increased specialization and the emergence of a cash economy.

In turn, the growth of towns and cities worked to help encourage the migration of non-agricultural workers from rural areas—especially artisans, traders, bar and restaurant owners, shop-keepers and construction workers—thus effectively becoming a “pull” factor for prospective migrants. This continued through the post-war period, where the combination of the consolidation and centralization of government structures, the renewed emphasis on road building, the emergence of industrial enterprises and commercial centers, the designation of industrial zones along the railroad, among other things, led to increased urban growth, especially the emergence of small commercial towns.

¹ This section draws substantially on World Bank (2007: Ch 4), where more details can be found.

In addition to the rural-urban migration, however, Ethiopia started experiencing increased rural-rural migration, also. This was especially linked to the emergence of commercial agricultural sites. In 1976, for example, 75 percent of the farm workers engaged in 16 irrigation schemes in the Awash valley were immigrants, mostly from areas of considerable land-pressure (World Bank, 2007: 116)—that is, rural areas. Similarly, the development of coffee production in the south-west also attracted labor, both seasonal and permanent, and also led to the development of new urban areas. In the early 1970s, for example, seasonal migration to the coffee areas was estimated at 50,000 (World Bank, 2007: 116). While the political and economic reforms starting in the 1970s—most notably the confiscation of private lands, the closure of private mechanized agriculture, the introduction of a pass system and check-points along the main highways—led to a temporary halt in migration and therefore also in the high urbanization rates, the intensified conflict led to the resumption of large inflows of migrants into cities between 1984 and 1994 (World Bank, 2007: 117).

Today people are, in principle, free to move freely within Ethiopia. There are two main constraints, however, namely social constraints (most notably concerning adult women) and the requirement to carrying a personal ID at all times. Additionally, movement from urban areas requires an official leaving letter from the local kebele², while movement from rural areas does not—though it is generally perceived that it would be useful to still clear a potential move with the local kebele prior to the move. Additionally, while there does not appear to be any formal rules on the matter, it appears to be widely perceived that migration beyond a certain duration will result in the forfeit of land rights for the migrant(s) concerned (World Bank, 2007: 118).

As a result, internal migration continues to play a role in Ethiopia today. Both push and pull factors are important in motivating migrants, who frequently are very different than non-migrants regarding their skills, education and intrinsic characteristics—after all, they decided to move, while those who remained in their village, town or city did not.

3. Methodology

To help frame the subsequent analysis, we consider a conceptual framework in which wages are determined by education and other characteristics, including migration status. In essence, this is an augmented Becker-Mincer human capital model in which migration status is considered as a

² The smallest administrative unit of Ethiopia (corresponds to a ward or neighborhood).

particularly important correlate of wages. Specifically, wages are assumed to be a function of education (E); other observed individual background characteristics including age, gender and geographical location (B); and migration status and the share of migrants in the (current) community (M), giving rise to the following wage function:

$$W = W(E, B, M) \tag{1}$$

In (1), an increase in education leads to an increase in wages, as well, holding the other factors constant. In addition to this standard result from the Becker-Mincer framework, the inclusion of migration variables allows for different returns to migrants and non-migrants and for an influx of migrants to affect wages, holding the other factors constant.

Based on the previous discussion we will explore the following four questions in the empirical analysis. First, is there a premium to migration? In other words, are wages and migration status positively correlated? Here, one might conjecture a positive relationship, since migrants may have more diverse labor market experience, for example, essentially bringing with them their labor market experience from their “old” community. Second, does the share of migrants in the current community matter? Here, one might expect a negative association between the share of migrants in the community and individual wages, due to the increased competition from migrants depressing wages. Third, is the overall wage structure of migrants and non-migrants different? For example, one might expect the returns to education to be higher for migrants, again due to them effectively bringing with them a more diverse labor market experience (i.e. labor market experience both from the current community and the community of origin). Fourth, does the migration-wage association differ across educational attainment? For example, one might expect the less educated to be harder hit—in terms of their wages—by and influx of migrants.

Moving to the estimation strategy, it is not clear a priori how exactly (1) should be estimated empirically. For example, (1) can only be estimated for individuals receiving a wage—making the sample a select one, or similarly, implying that labor supply is endogenous. To explore this further, we initially experimented with Heckman-type models to allow labor supply to be endogenous, using variables for children in the household, marital status and marital status interacted with gender to identify the selection equation but found only modest evidence supporting this more complicated – and assumption intensive – estimation procedure.

Another issue is the potential endogeneity of migration status—stemming from the fact that our migration status measure is potentially prone to simultaneity, measurement error, and omitted variables issues. Hence, in a model where only household level migration was included, we also experimented with endogenizing migration status of the household, using the density of migrant households in the community of residence. This, too, turned out to support the more straightforward OLS framework. OLS is therefore the preferred method of estimation. Even so, we emphasize that one should still be careful not to attribute an explicit causal interpretation to subsequent results—but rather treat them as suggestive of one or more causal mechanisms being at play.

In addition to the full sample of adult Ethiopian wage earners—so as to address the research questions mentioned previously—models are also estimated separately for females and males, migrants and non-migrants, as well as by educational attainment so as to explore the possibility of the wage structure differing across these dimensions, especially as pertaining to the migration and education variables. The main objective here is to determine which part(s) of the Ethiopian work force are particularly affected by migration.

To incorporate the survey design and make the results nationally representative, the estimations incorporate sampling weights, stratification and clustering (Froot, 1989; Williams, 2000)—where the latter implicitly additionally allows for arbitrary heteroskedasticity, by also estimating Huber-White standard errors (Huber, 1967; White, 1980).

4. Data and Descriptive Analysis

The empirical analyses of this paper examine household survey data for Ethiopia. The Ethiopia Child Labour Force Survey (CLFS) is a nationally representative multi-purpose household survey, carried out in 2001. The household survey contains information on household migration, wages, educational attainment, as well as information on background variables such as age, gender, tribal association/ethnicity and region of residence, which are also important factors in analyses of wage formation and migration.

The wage measure (the dependent variable) is based on information on cash and in-kind payments and the period/term of payment, thus allowing us to create a variable for hourly total

wages.³ Initial tabulations of the wage measure revealed some extreme observations in the upper tail of the wage distribution, so we trimmed off all wages 65 birr/hour and above⁴—which, however, amounts to less than 0.5 percent of the effective estimation sample.

Among the explanatory variable, the main variable of interest is migration status. The migration status measure is based on information on household level migration. Specifically, the Survey asks “Has this household ever lived outside of this town/rural part of this wereda as usual residence?” If so, the Survey goes on to ask “How long has this household been living in the present place of residence?” Response categories include less than a year, one year, two years, and so on. We construct a (binary) measure of recent migration, which is defined as one if the household has been living in the current location for 4 years or less, and zero otherwise.

One potential issue with this is that this measure implicitly assumes that all household members “share” the migrant status. Contrary to this, the Ethiopia Labour Force Survey (LFS) from 1999 includes information on individual level migration status. The LFS, however, does not include wage or earnings information. While household level migration information might be thought to overstate individual level migration status by implicitly applying to all household members, the wording of the question in the CLFS on which this information is based on at the same time seems somewhat restrictive, talking about “the” household. It is therefore not a priori clear whether our measure overstates or understates “true,” individual level migration.

To provide a rough check of the validity of approximating individual level migration status with this household based measure, we compare the incidence of recent migration in the LFS and the CLFS (Table 1). Being only two years apart, there should not be really massive differences in the incidence in recent migration – if our household based migration measure is valid. While Table 1 reveals differences in the migration incidence when comparing the two measures – with the LFS consistently yielding a higher migration incidence than the CLFS – the results do not appear irreconcilable. With the caveat that the measure is systematically downwards biased relative to individual level migration, we therefore proceed with our household based migration measure.

³ Except for workers reporting “piece rate” as the period/term of payment, since no information is collected on the work hours associated with total earnings for this case.

⁴ In 2001 (the year of the survey) the exchange rate was about 8.5 birr to 1 USD.

[Table 1 about here]

In addition to the migration status variable, we also include a variable for the share of migrants in the community. This is defined using the migration status variable, so that we effectively have to assume that all members of a “migration household” are also all themselves migrants. Again, this variable is an attempt to measure the potential competition from in-migrants.

Education variables obviously have a prominent role in the human capital framework. We define this as a series of dummy variables, based on information on the highest grade completed. Due to the many categories (including grades 1-12, university, literacy campaigns, etc), we create a total of six dummies: No education (reference), Grade 1-4, Grade 5-8, Grade 9-12, Above grade 12, and Literacy campaign and other non-formal education.

Additionally, we include a full set of dummy variables for region of residence. These capture a host of factors associated with region of residence, including quality of education and local labor market conditions. Again, while we are not specifically interested in these factors per se, rendering the results pertaining to migration and education net of these factors helps decreasing any bias of the pertinent coefficients.

The sample is initially restricted to employed adults 15 years of age living in urban areas, who were not piece rate enumerated.⁵ This yields an initial, potential estimation sample of 10,511 observations. Due to the trimming of wages and missing observations on one or more of the explanatory variables the final, actual estimation sample contains 10,414 observations.

After now discussing the variable definitions and sample restrictions, it seems fruitful to get a first look at the data in terms of sample means in various dimensions. First, it would seem interesting to explore the reasons why people in the sample migrate in the first place. From Table 2, people predominantly move for work-related reasons, either to look for a job (about 20 percent) or because they actually found a job and/or received a job transfer (about 62 percent).

[Table 2 about here]

Next, how are the full sample, females, males, migrants, and non-migrants faring in terms of wages, education, and migration status (if applicable)? From Table 3, male wages exceed female wages (again, a well-established phenomenon for developed and developing countries alike)—more importantly for our purposes, the raw wage gap seems to favor migrants heavily, at

⁵ Again, as discussed earlier, hourly wages cannot be calculated for piece rate workers for this dataset.

almost 25 percent higher hourly wages than non-migrants. In addition to the higher wages on average, migrants are also more educated than non-migrants on average. So, based on the descriptive statistics, migrants seem to be better faring than non-migrants than non-migrants, both in terms of human capital and wages. However, this is based on simple correlations and does not take into account other variables—for example, migrants may not obtain higher wages when other factors are controlled for (including their human capital); likewise, migrants may not necessarily have higher returns to their human capital than non-migrants. To examine issues such as these, a multivariate empirical analysis is called for—to which we therefore now turn.

[Table 3 about here]

5. Multivariate Analysis

This section presents and discusses reduced form estimates of wage determinants focusing at the relationship between wages and migration. The estimations are carried out as reduced form OLS⁶ Mincer-type wage regressions, extended with household migration status (except when conditioning on migrant status) and the share of migrants in the community. In addition to the full sample of adult Ethiopian wage earners, models are also estimated separately for females and males, migrants and non-migrants, as well as by educational attainment so as to explore the possibility of the wage structure differing across these dimensions, especially as pertaining to the migration and education variables. The main objective here is to determine which part(s) of the Ethiopian work force are particularly affected by migration. All estimations incorporate the survey design—thus making the results nationally representative—by incorporating sampling weights, stratification and clustering. The latter implicitly also allows for arbitrary heteroskedasticity, by effectively estimating Huber-White standard errors (Huber, 1967; White, 1980). To allow for the possibility that observations are correlated within communities the standard errors are also adjusted for within-cluster correlation (Froot, 1989; Williams, 2000).

Is there a premium to migration? Does the share of migrants in the current community matter?

From Table 1, migration is associated with substantively and statistically significantly higher

⁶ Again, as discussed in Section 2, the potential endogeneity of both labor supply and migration status is a relevant concern in this study—though initial experiments with Heckman-type models to allow labor supply to be endogenous, as well as an instrumental variables strategy in a model where only household level migration was included (using the density of migrant households in the community of residence as identifying instrument) both turned out to support the more straightforward OLS framework.

wages for the full sample and for males, so that males from households, who moved to the area within the past 4 years, earn about 14 percentage-points more than comparable males from non-migrant households. At only 4 percentage points, the migration premium for females is much lower; it is also imprecisely measured and therefore not statistically significant. Though the estimate is large, with an expected negative sign, there is no statistically significant association between the share of recent migrants in the community of destination and wages. Further, many of the findings from the empirical human capital literature are seen to hold for Ethiopia, as well. There is a wage gap in wages related to gender, females earning considerably less than males for given characteristics, a concave age-earnings profile as well as substantial returns to education. Additionally, education returns increase with the education level. The wage structures are also statistically significantly differently across females and males overall: performing a Chow-type test for structural break, thus testing whether the interactions in a fully interacted model are jointly zero yields a p-value less than 0.01 percent. The wage structure therefore differs statistically significantly between females and males.

[Table 4 about here]

Is the overall wage structure of migrants and non-migrants different?

While only males from migrant households were found to earn substantially more than comparable individuals (males) from non-migrant households, there is still the possibility that the entire returns structure differs systematically between individuals from migrant and non-migrant households. To examine this further, we estimate the models separately for migrants and non-migrants (see Table 2). From Table 2, female migrants experience higher returns to education than female non-migrants while the evidence for males is more mixed. Noticeably, for the full sample, the depressing effect of having more migrants in the community is now both large and statistically significant for migrants, while it remains statistically insignificant – and much smaller in substantive terms – for non-migrants.

[Table 5 about here]

We again formally test whether the wage structure differs between migrants and non-migrants. This yields p-values of 2 percent for the full sample, 7.8 percent for females, and 14.3 percent for males. There is therefore strong evidence for structural differences in the wage structure for wage earners as a whole. Conditioning on gender, however, there is moderate to

string evidence favoring structural differences in the wage structure of female migrants and female non-migrants and weak to no evidence favoring a similar difference in the wage structure for males.

Does the migration-wage association differ across educational attainment?

To explore whether the migration-wage association differs across educational attainment, we estimate models conditioning on educational attainment. Table 3 presents the results pertaining to the migration variable(s) from this exercise (the other explanatory variables were included as before but the results have been excluded to make the table more readable; they are available upon request). Table 3 reveals two striking results. First, the positive premium to household level migration found earlier for the full sample and for males only “survives” – in statistical terms, it remains substantively large for several of the other education levels – for the group of individuals with above grade 12 completed. Second, the depressing effect of having more migrants in the community found earlier for migrants in the full sample turns out to be driven by the less skilled workers: while substantively large for several of the different education levels, the negative association is only statistically significantly different from zero for individuals with no education (full sample, females, males, non-migrants) and for individuals with grade 1-4 completed (migrants). Testing for whether the wage structure was also statistically significantly as a whole across educational attainment revealed that this was indeed the case: the p-value for joint statistical significance of the interaction terms in a fully interacted model was less than 0.001 in all cases.

In combination, these last results suggest that the more educated are the winners from increased migration, while the less educated are the losers.

[Table 6 about here]

6. Conclusion

This paper examines internal migration in Ethiopia, focusing at the linkages among internal migration, human capital and wages. Descriptive statistics indicate that migrants are better off than non-migrants on average in terms of both their human capital and their wages. When moving to the multivariate analysis, these preliminary results are strengthened: not only do migrants also obtain higher wages when other factors (including human capital) are controlled

for, they also obtain higher returns to their human capital than non-migrant, controlling for other factors.

What does all this mean? In combination, the results suggest that the more educated are the winners from increased migration, while the less educated are the losers. That is, “the winner takes it all”: the more educated reap higher returns both from benefitting more from migration and from being better educated to begin with, leaving the less educated—especially among the migrant population—as the losers.

This result should be of concern to policy makers in Ethiopia, since individuals with low levels of human capital already is a vulnerable group. Focus should therefore be shifted even more towards this group – for example in terms of skills upgrading and education – especially in areas with high levels of in-migration.

Future research may want to extend these analyses to other countries—especially in Sub-Saharan Africa, where internal migration is an important component of the labor market. As always, such efforts are data dependent, however. The data examined here provided only a measure of internal migration at the household level, which—our cross-validation efforts notwithstanding—is less than ideal. Collecting migration information at the individual level in future surveys for Ethiopia—and other countries—would help us understanding the workings and correlates of internal migration even better.

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Table 1. Incidence of Recent Migration – Total and By Gender, for All Individuals, Adults and Adult Household Heads, LFS 1999 and CLFS 2001

	<i>LFS 1999</i>		<i>CLFS 2001</i>	
	<i>Mean</i>	<i>95 percent CI</i>	<i>Mean</i>	<i>95 percent CI</i>
<i>Adults & children combined:</i>				
Full sample	0.043	0.039; 0.046	0.025	0.022; 0.028
Females	0.046	0.043; 0.050	0.024	0.021; 0.027
Males	0.039	0.036; 0.043	0.025	0.022; 0.028
<i>Adults (15+):</i>				
Full sample	0.057	0.053; 0.061	0.028	0.025; 0.031
Females	0.061	0.057; 0.066	0.026	0.023; 0.029
Males	0.052	0.048; 0.057	0.029	0.026; 0.033
<i>Adult household heads:</i>				
Full sample	0.057	0.042; 0.050	0.036	0.032; 0.040
Females	0.061	0.050; 0.063	0.044	0.038; 0.051
Males	0.052	0.038; 0.046	0.033	0.029; 0.037

Notes: Calculations incorporate sampling weights and clustering (Froot, 1989; Williams, 2000).

Source: Ethiopia Labour Force Survey, 1999, and Ethiopia Child Labour Survey, 2001.

Table 2. Reason for Migration, Full Sample and by Gender

	<i>All</i>	<i>Females</i>	<i>Males</i>
Education	0.044	0.072	0.033
Marriage arrangement	0.008	0.006	0.009
Divorce	0.009	0.032	0.000
Looking for a job	0.199	0.182	0.206
Found a job/transfer	0.616	0.546	0.645
Displacement, war, draught	0.051	0.069	0.044
Other	0.073	0.094	0.064
Total	1.000	1.000	1.000

Notes: Sample sizes are 1, 147 observations (all migrants), 349 observations (female migrants), and 798 observations (male migrants). Calculations incorporate sampling weights.

Source: Ethiopia Child Labour Survey, 2001.

Table 3. Means for Estimation Sample: Full Sample and by Gender and Migrant Status

	<i>All</i>	<i>Female</i>	<i>Males</i>	<i>Migrants</i>	<i>Non-migrants</i>
Hourly earnings	3.209	3.009	3.344	4.022	3.110
Female	0.405	1.000	0.000	0.296	0.418
Age	31.982	27.773	34.841	31.072	32.092
No education	0.184	0.305	0.102	0.135	0.190
Grade 1-4	0.084	0.092	0.079	0.055	0.088
Grade 5-8	0.186	0.154	0.207	0.148	0.190
Grade 9-12	0.286	0.262	0.302	0.315	0.283
Above grade 12	0.237	0.167	0.285	0.327	0.226
Lit camp/nonformal	0.022	0.020	0.024	0.019	0.023
Recently migrated	0.108	0.079	0.127	1.000	0.000
Share migrants	0.085	0.082	0.087	0.177	0.074
N	10, 414	4, 228	6, 186	1, 147	9, 267

Notes: Calculations incorporate sampling weights.

Source: Ethiopia Child Labour Survey, 2001.

Table 4. Wage Regressions for Full Sample and Across Gender

	<i>Full sample</i>	<i>Females</i>	<i>Males</i>
Female	-0.395*** [0.032]		
Age	0.088*** [0.008]	0.087*** [0.015]	0.088*** [0.009]
Age squared	-0.001*** [0.000]	-0.001*** [0.000]	-0.001*** [0.000]
Grade 1-4	0.220*** [0.060]	0.178** [0.080]	0.183** [0.085]
Grade 5-8	0.634*** [0.057]	0.566*** [0.085]	0.581*** [0.079]
Grade 9-12	1.076*** [0.051]	1.205*** [0.065]	0.907*** [0.077]
Above grade 12	1.638*** [0.051]	1.808*** [0.073]	1.471*** [0.072]
Lit camp/nonformal	0.099 [0.110]	-0.066 [0.157]	0.129 [0.151]
Recently migrated	0.097* [0.051]	0.04 [0.109]	0.141*** [0.053]
Share migrants	-0.304 [0.297]	-0.381 [0.424]	-0.215 [0.305]
Tigray	0.680*** [0.259]	0.898** [0.353]	0.480** [0.206]
Affar	0.502*** [0.174]	0.730*** [0.260]	0.302*** [0.108]
Amhara	-0.239*** [0.052]	-0.318*** [0.085]	-0.189*** [0.060]
Oromyia	-0.214*** [0.049]	-0.222*** [0.068]	-0.238*** [0.058]
Somali	0.11 [0.104]	0.263*** [0.081]	0.016 [0.161]
Benishangul	-0.072 [0.090]	0.057 [0.244]	-0.162** [0.069]
SNNP	-0.190*** [0.054]	-0.129 [0.091]	-0.239*** [0.062]
Gambella	0.082 [0.083]	0.236** [0.093]	0.02 [0.109]
Harari	-0.017 [0.040]	0.027 [0.059]	-0.059 [0.052]
Dire Dawa	0.133* [0.075]	0.272** [0.110]	0.026 [0.072]
Constant	-2.105*** [0.130]	-2.542*** [0.217]	-1.951*** [0.181]
R ²	0.44	0.39	0.37
N	10, 414	4, 228	6, 186

Notes: Robust Huber-White (Huber, 1967; White, 1980) standard errors, adjusted for within-cluster correlation/clustering (Froot, 1989; Williams, 2000), in brackets under parameter estimates. *: statistically significant at 10 percent; **: statistically significant at 5 percent; ***: statistically significant at 1 percent. Reference groups are “No education” (education), and “Addis Ababa”

(region). Chow-type test for sample split across gender: $F(19, 505) = 3.90$, $P\text{-value} < 0.001$.
Source: Ethiopia Child Labour Survey, 2001.

Table 5. Wage Regressions By Migrant Status -- Full Sample and Across Gender

	<i>Full sample</i>		<i>Females</i>		<i>Males</i>	
	<i>Migrants</i>	<i>Non-migrants</i>	<i>Migrants</i>	<i>Non-migrants</i>	<i>Migrants</i>	<i>Non-migrants</i>
Female	-0.399*** [0.113]	-0.393*** [0.033]				
Age	0.116*** [0.024]	0.087*** [0.008]	0.156** [0.061]	0.085*** [0.015]	0.105*** [0.027]	0.087*** [0.010]
Age squared	-0.001*** [0.000]	-0.001*** [0.000]	-0.002** [0.001]	-0.001*** [0.000]	-0.001*** [0.000]	-0.001*** [0.000]
Grade 1-4	0.521* [0.294]	0.199*** [0.062]	0.618* [0.350]	0.152* [0.084]	0.18 [0.433]	0.186** [0.090]
Grade 5-8	0.871*** [0.241]	0.618*** [0.059]	1.082** [0.482]	0.525*** [0.092]	0.471 [0.324]	0.596*** [0.086]
Grade 9-12	1.328*** [0.221]	1.053*** [0.054]	1.461*** [0.272]	1.181*** [0.070]	0.935*** [0.310]	0.901*** [0.081]
Above grade 12	1.811*** [0.209]	1.619*** [0.054]	2.095*** [0.277]	1.778*** [0.079]	1.401*** [0.299]	1.476*** [0.078]
Lit camp/nonformal	0.505* [0.269]	0.076 [0.116]	1.212 [0.914]	-0.104 [0.160]	0.022 [0.355]	0.149 [0.166]
Share migrants	-0.969** [0.408]	-0.15 [0.333]	-1.226 [0.806]	-0.206 [0.461]	-0.705 [0.530]	-0.102 [0.351]
Tigray	0.729** [0.310]	0.667** [0.261]	1.172** [0.484]	0.822** [0.335]	0.395 [0.300]	0.511** [0.219]
Affar	0.167 [0.178]	0.554*** [0.194]	-0.033 [0.376]	0.783*** [0.256]	0.179 [0.233]	0.334** [0.129]
Amhara	-0.041 [0.207]	-0.279*** [0.061]	-0.111 [0.422]	-0.351*** [0.104]	-0.02 [0.216]	-0.231*** [0.063]
Oromyia	-0.18 [0.144]	-0.226*** [0.053]	-0.186 [0.235]	-0.235*** [0.068]	-0.249 [0.196]	-0.246*** [0.064]
Somali	-0.081 [0.182]	0.17 [0.110]	0.344* [0.203]	0.268*** [0.088]	-0.161 [0.210]	0.11 [0.188]
Benishangul	0.05 [0.186]	-0.103 [0.105]	-0.231 [0.273]	0.134 [0.267]	0.095 [0.258]	-0.231*** [0.077]
SNNP	-0.134 [0.191]	-0.196*** [0.053]	-0.121 [0.263]	-0.13 [0.094]	-0.199 [0.262]	-0.247*** [0.059]
Gambella	0.012 [0.158]	0.099 [0.091]	0.161 [0.260]	0.249** [0.106]	-0.14 [0.224]	0.047 [0.122]
Harari	0.055 [0.201]	-0.022 [0.039]	-0.11 [0.511]	0.034 [0.058]	0.089 [0.236]	-0.071 [0.055]
Dire Dawa	0.064 [0.186]	0.131* [0.077]	-0.126 [0.345]	0.275** [0.112]	0.03 [0.260]	0.02 [0.075]
Constant	-2.562*** [0.461]	-2.082*** [0.133]	-3.606*** [0.802]	-2.502*** [0.226]	-1.988*** [0.703]	-1.943*** [0.183]
R ²	0.45	0.44	0.42	0.39	0.37	0.36

N	1, 147	9, 267	349	3, 879	798	5, 388
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Notes: Robust Huber-White (Huber, 1967; White, 1980) standard errors, adjusted for within-cluster correlation/clustering (Froot, 1989; Williams, 2000), in brackets under parameter estimates. *: statistically significant at 10 percent; **: statistically significant at 5 percent; ***: statistically significant at 1 percent. Reference groups are “No education” (education), and “Addis Ababa” (region). Chow-type tests for sample split: F(19, 505) = 1.80, P-value = 0.020 (full sample); F(18, 506) = 1.52, P-value = 0.078 (females); F(18, 506) = 1.37, P-value = 0.143 (males).

Source: Ethiopia Child Labour Survey, 2001.

Table 6. Wage Regressions by Educational Attainment – Full Sample, Across Gender, and Across Migrant Status

	<i>No education</i>	<i>Grade 1-4</i>	<i>Grade 5-8</i>	<i>Grade 9-12</i>	<i>> Grade 12</i>	<i>Non-formal</i>
<i>(i) Full sample:</i>						
Recently migrated	0.003 [0.225]	0.155 [0.257]	0.035 [0.145]	0.073 [0.075]	0.126* [0.068]	0.074 [0.242]
Share migrants	-1.744*** [0.498]	-0.345 [0.654]	-0.274 [0.782]	0.166 [0.391]	0.113 [0.295]	0.472 [2.242]
R ²	0.18	0.32	0.2	0.18	0.16	0.29
N	1, 810	861	2, 133	3, 187	2, 206	217
<i>(ii) Females:</i>						
Recently migrated	-0.112 [0.303]	0.148 [0.367]	0.404 [0.446]	-0.021 [0.158]	0.005 [0.087]	1.24 [1.203]
Share migrants	-1.527** [0.712]	0.648 [1.185]	-1.169 [1.095]	0.153 [0.575]	0.308 [0.342]	-0.984 [3.058]
R ²	0.12	0.28	0.17	0.21	0.12	0.12
N	1, 237	391	747	1, 167	612	74
<i>(iii) Males:</i>						
Recently migrated	0.34 [0.366]	0.23 [0.271]	-0.134 [0.187]	0.133 [0.084]	0.160** [0.079]	-0.091 [0.266]
Share migrants	-2.599*** [0.829]	-0.812 [0.743]	0.136 [0.823]	0.145 [0.408]	0.027 [0.315]	0.678 [2.694]
R ²	0.18	0.27	0.12	0.12	0.14	0.34
N	573	470	1, 386	2, 020	1, 594	143
<i>(iv) Migrants:</i>						
Share migrants	-2.32 [1.863]	-3.077** [1.252]	-1.794 [1.599]	-0.037 [0.462]	-0.46 [0.653]	-2.75 [2.904]
R ²	0.3	0.26	0.25	0.33	0.23	0.56
N	143	80	197	349	359	19
<i>(v) Non-migrants:</i>						
Share migrants	-1.612*** [0.561]	0.012 [0.703]	0 [0.826]	0.331 [0.461]	0.265 [0.300]	0.313 [2.488]
R ²	0.17	0.35	0.21	0.17	0.16	0.31
N	1, 667	781	1, 936	2, 838	1, 847	198

Notes: Robust Huber-White (Huber, 1967; White, 1980) standard errors, adjusted for within-cluster correlation/clustering (Froot, 1989; Williams, 2000), in brackets under parameter estimates. *: statistically significant at 10 percent; **: statistically significant at 5 percent; ***: statistically significant at 1 percent. Other explanatory variables as in Tables 4 and 5. Chow-type test for sample splits: F(74, 450) = 5.81, P-value < 0.001 (full sample); F(68, 456) = 11.65, P-value < 0.001 (females); F(69, 455) = 3.49, P-value < 0.001 (males); F(65, 459) = 12.33, P-value < 0.001 (migrants); F(69, 455) = 4.53, P-value < 0.001 (non-migrants).

Source: Ethiopia Child Labour Survey, 2001.