Labor markets in transforming agricultural economies:

The case of Ethiopia

Abstract

Africa’s economies are transforming but it is not well understood to what extent this is affecting rural and agricultural labor markets. This is important given that the large majority of Africans make a living in these areas. Based on a large-scale household survey in Ethiopia, we find that hired labor use in agriculture is relatively low, that wage income - in the agricultural and non-agricultural sector - accounts for about 10 percent of total household income, and that real rural wages increased by two-thirds over the last fifteen years, mostly driven by high agricultural growth. Moreover, the use of agricultural labor markets and wage increases were higher in areas close to cities, important given rapid urbanization in Ethiopia (and most of Africa). The wage increases are good news for the poor but it also induces adjustments in agricultural production practices, including increased adoption of labor-substituting technologies such as herbicides and mechanization. These findings are important for the debate on structural and agricultural transformation and rural job creation in the country.
1. **Introduction**

Understanding and stimulating the off-farm economy is deemed important towards improving the welfare of rural residents in developing economies. Particularly, the development of well-functioning rural labor markets is increasingly seen as crucial for economic growth and the creation of livelihood opportunities for the youth (Fox et al., 2013). Moreover, increases in rural wages are found in a number of developing countries to be strongly linked with poverty alleviation given that the poorest part of the population, the majority of which reside in rural areas, regularly depend on such wages for their livelihood (Ravallion, 2000; Lanjouw and Lanjouw, 2001). It is therefore important to understand how rural labor markets work and to what extent they are transforming in these settings in developing countries and particularly in Africa.

We look at this issue in the case of Ethiopia, the second most populous country in Africa. Ethiopia’s economy grew rapidly over the last decade. Despite this fast change in the economy, more than three-quarters of its population still makes a living in the agricultural sector (Schmidt and Bekele, 2016). While quick transformation has occurred in different segments of its economy including agriculture (Bachewe et al., 2018; World Bank, 2015), it is not well understood what the implications of this growth have been on labor market and rural wage developments. In other developing economies such incomes have been shown to become increasingly important in rural areas during periods of rapid growth (Haggblade et al., 2007).

This study provides new insights on labor markets and wages in rural Ethiopia using uniquely detailed recent household survey datasets and nationally representative agricultural production and price datasets covering the 2004-2018 period. In particular, this study addresses the following two broad research questions. First, how important is wage income in rural Ethiopia and what are the factors associated with agricultural wages and wage labor use? Second, to what
extent are rural wages changing and what are the drivers and implications of the observed changes?

We find that wage income accounts for 10 percent of the total rural household income and that this is largely agricultural wage income, illustrating the large reach of agriculture in these rural areas. Wage labor is found to be more important for better connected areas to cities, an important finding given large changes in infrastructure and urbanization in the country (see also Fafchamps and Shilpi, 2003; 2005). We further find that rural wages are on the rise, mostly driven by agricultural growth in the country, and that rises have been higher in areas close to cities and in zones covered by the social safety net (the biggest safety net in Africa, except South-Africa) though the impact of the latter is small in magnitude. These rural wage rises are shown to affect poverty and agricultural production practices, more in particular on incentives for the adoption of labor-saving technologies - such as herbicides and mechanization - that have rapidly taken off in recent years (Tamru et al., 2017; Berhane et al., 2017). These findings have important implications for the policy debate on structural and agricultural transformation and job creation in the country.

The paper contributes to the international literature in several ways. First, we illustrate the rapid increase in real rural wages in one of the poorest and least urbanized countries in the world, using innovative appropriate methods for deflating. Second, an important driver of the rise is shown to have been agricultural growth. While most of the previous literature has focused on illustrating the important impacts of the pull of urban areas and Lewis’ turning point dynamics (e.g. Zhang et al., 2014), we also show that connectivity to cities is in Ethiopia an important associate for increasing reliance on wage labor markets as well as for levels of wages paid, indicating that the rapid urbanization that is noted in most African countries is seemingly an important engine for such agricultural and rural labor market dynamics. Third, we show strong
linkages of wage increases and poverty reduction, confirming (scarce) research in other - but mostly Asian - countries (e.g. Lanjouw and Murgai, 2009).

The paper is organized as follows. In section two we discuss the datasets used in the study. In section three, we present the conceptual framework used to study factors associated with rural wages and agricultural labor demand. In section four we describe the importance of wage income and hired-in agricultural labor, and present results on the associates of using hired-in agricultural labor and of wages. Results of analyses on trends, drivers of changes in rural wages, and implications of the observed changes are discussed in section five. We conclude in section six.

2. Data

This study mainly uses three data sources: 1) monthly retail and producer price series; 2) annual data on agricultural and manufacturing output (by zone); and 3) household data collected in the Agricultural Growth Program baseline survey. These datasets are discussed consecutively.

First, the Central Statistical Agency (CSA) has been collecting since 1996 monthly retail price data from about 120 markets in small and large rural towns as well as major urban centers in 66 of the 94 administrative zones located in all 11 regions of Ethiopia. Out of over 500 items in the dataset we use wages of casual laborers and prices of a number of consumer food and non-food items. We deflate nominal wages and other prices using the regional general consumer price index data from CSA (CSA, 2016c). We also use the poor-persons’ general consumer price index (PP-GCPI) to deflate nominal prices. The PP-GCPI is constructed using the retail price dataset described above and CSA’s Household, Income, Consumption, and Expenditure Survey (HICES) dataset of 2004/05 (CSA, 2007) on expenditure shares on 26 food and non-food categories (over 400 items), which CSA uses to compute the regional average prices indices. We define the poor
as the bottom two quintiles of the aggregate expenditure measure. The poor persons’ general and food-price indices are computed using the formula:

\[
P_{w,t} = \sum_{n=1}^{N} s_{n,w} \cdot \bar{p}_{n,w,t}
\]

where \( w \) indexes woredas/districts, \( t \) denotes months, and \( n \) denotes the food and non-food items, \( s_{n,w} \) denotes the expenditure share of item \( n \), and \( \bar{p}_{n,w,t} \) the average price of \( n \) (see also Headey et al., 2012). The index is set with December 2011 as the base period to match with regional GCPI.

Second, CSA collects the producer price series from markets in small towns and rural areas sampled to represent 72 predominantly rural zones located in 10 regions, excluding Addis Ababa, the capital city. CSA has been collecting data on prices of about 110 producer items since 1996 in a manner similar to retail prices. For instance, for each producer item three price observations are made by interviewing producers, consumers, and/or wholesalers. We use a simple annual average of 68 crop varieties to value crop outputs and sales. We also use data on regional total manufacturing output (CSA, 2016), which CSA collects through its annual census of small, medium, and large manufacturing enterprises. Furthermore, we use data obtained from CSA annual reports on zonally aggregated crop output (CSA, 2005a-2015a) and proportion of crop output sold (2009c-2015c). CSA collects these data through its annual Agricultural Sample Survey (AgSS) of over 40,000 agricultural households. During the period studied the surveys covered or are representative of “the entire rural parts of the country except the non-sedentary population of three zones of Afar and six zones of Somali regions” (CSA, 2005a-2015a).

The analyses in this study use four variables constructed from these data. We compute the real value of per capita zonal grains as well as cereal output by multiplying zonal aggregate grain/cereal output by PP-GCPI deflated average annual producer crop prices and dividing that by
population size (CSA, 2009d; 2013d). The third variable, per capita value of crop output sold, is similarly computed using data on zonal average proportion of crop output sold. Finally, we compute regional per capita real manufacturing output using the data on value of regional total manufacturing output, PP-GCPI, and population size.

Third, data collected in the Agricultural Growth Program of Ethiopia (hereafter AGP) baseline survey is the other important dataset used. The AGP baseline survey dataset was collected from woredas with relatively high agricultural potential in four regions of the country: Tigray, Amhara, Oromiya, and Southern Nations, Nationalities, and Peoples’ (SNNP) regions. Woredas were designated as high agricultural potential and selected for initial and subsequent targeting by the AGP using multiple criteria including: natural resource endowments, suitability of rainfall and soil, and access to markets. Consequently, the sampling frame of the AGP baseline survey included woredas in the four regions that were not covered by the Productive Safety Net Programme (PSNP), a program that covers food insecure districts in the country. The survey was conducted in May 2011 and covered 7,928 households, sampled to represent over 9 million households in 93 woredas. Finally, we use zonal poverty head count index data obtained from Hill and Tsehaye (2014).

3. Conceptual framework

Building on Strauss’ (1986) general household model, we consider a representative rural household that consumes four items: agricultural good \(C_A\), home-produced non-agricultural good \(C_E\), a market purchased manufactured good \(C_M\), and leisure \(l\). The household’s optimization problem is given as:

\[
\text{Max}_{C_A, C_E, C_M, l} \quad U(C_A, C_E, C_M, l)
\]

subject to
\[ P_M C_M \leq P_A (Q_A - C_A) + P_E (Q_E - C_E) + W (F_O - L_I - L_E) \]  \hspace{1cm} (2)

\[ Q_A = f(T, F_A, L_I) \]  \hspace{1cm} (3)

\[ Q_E = g(F_E, L_E) \]  \hspace{1cm} (4)

\[ F_A + F_E + F_O + l = F \]  \hspace{1cm} (5)

where \( P_M, P_A, \) and \( P_E \) denote prices of manufactured, agricultural, and non-agricultural goods, respectively. \( W \) stands for market wage rate, \( T \) for land used in agricultural production and \( Q_j \), where \( j \in (A, E) \), stands for agricultural (A) and non-agricultural (E) outputs. Similarly, \( L_j \) and \( F_j \) stand for hired-in and family labor, respectively, used in \( j \). \( F_O \) stands for hired out family labor.

Equations (3) and (4) imply that hired-in and family labor may not necessarily be perfect substitutes.\(^{10}\) Equation (2) indicates that the value of manufactured goods consumed is constrained by the household’s full income, which is the sum of agricultural and non-agricultural output and net wage income (hired-out wage income less hired-in labor cost).

Substituting equations (3)-(5) into (2) provides:

\[ P_M C_M + P_A C_A + P_E C_E + W l \leq \pi + WF \]  \hspace{1cm} (6)

The sum on the left side is the value of consumer goods and leisure time valued at the market wage rate. The right-hand side is the sum of the value of household members’ total endowment of time and total profits, \( \pi \). The latter is given by:

\[ \pi = (P_A Q_A + P_E Q_E) - W (F_A + F_E + L_A + L_E) \]  \hspace{1cm} (7)

In the current setup of the model, consumption and production decisions of the household are separable (Strauss, 1986). This implies that optimal levels of labor use and outputs obtained by maximizing (7) can be used in the maximization of the utility function (1) subject to equation (6). The first order conditions of (7) with respect to each type of labor is given as:

\[ \frac{\partial \pi}{\partial F_j} = 0 \rightarrow P_j \frac{\partial Q_j}{\partial F_j} = W \quad \text{for} \quad j \in (A, E) \]  \hspace{1cm} (8)
\[
\frac{\partial \pi}{\partial L_j} = 0 \rightarrow P_j \frac{\partial Q_j}{\partial L_j} = W \quad \text{for } j \in (A,E) \tag{9}
\]

Hired-in labor demand in the two production activities \((L_A \text{ and } L_E)\) are then solved as functions of parameters of the production functions, area of cultivated land, wages, and output prices. That is:

\[
L_j = L_j(T, P_A, P_E, W, X) \quad \text{for } j \in (A,E) \tag{10}
\]

\[
F_O = F_O(T, P_A, P_E, P_M, W, Y) \tag{11}
\]

In equation (10) the term X is included to account for other factors that influence hired-in labor demand through the production function. Household’s hired-out labor supply, equation (11), is solved using equation (5) after optimizing the utility function. Consequently, \(F_O\) is a function also of \(P_M\) and parameters of the utility function \((Y)\), in addition to those in equation (10).

We use the AGP baseline survey data to study the associates of hired-in labor demand and wage receipts. Although the dataset is remarkably detailed it lacks some of the information necessary to employ equations (10) and (11). In particular, data on family labor used in livestock production was not collected while data is available only on number of family members that worked (as opposed to labor input) in non-agricultural production, an activity that mainly involves home-processing and sales of food and drinks, and retailing of goods. However, data was collected on earnings from the activity net of all monetary costs. Taking the latter into account we modify equations (10) and (11) by including net earnings of non-agricultural production per worker (E) as:

\[
L_A = L_A(T, P_A, W, E, X) \tag{12}
\]

\[
F_O = F_O(T, P_M, P_A, W, E, Y) \tag{13}
\]

For each set of \(\{P_A, P_M, T, E, X, Y\}\) the total market demand for labor associated with each wage rate is derived as a sum of households’ labor demand or it is given as: \(\sum_{h=1}^{H} L_A^h\), where h indexes
households, \( h \in [1, 2, ..., H] \). Similarly, the supply of labor is given as: \( \sum_{h=1}^{H} F_{O}^{h} \). The equilibrium or market clearing wage rate is such that: \( \sum_{h=1}^{H} L_{A}^{h} = \sum_{h=1}^{H} F_{O}^{h} \) holds and is specified as:

\[
W = W(T, P_{A}, P_{M}, E, X, Y) \tag{14}
\]

We study the associates of hired-in labor using an empirical version of equation (12) while also highlighting factors associated with hired-out labor supply using an empirical version of (13). The framework developed in this section will be used in an important way to study the associates and drivers of rural wage formation. For this purpose we use three alternative empirical specifications of equation (14). We first investigate whether individual characteristics, types of agricultural task, and local economic factors are associated with wage receipts of workers that hired out labor. We then study whether local and aggregate economic factors have contributed to changes in rural wages observed during the 2004/5-2014/15 period using nationally representative zonally aggregated data from CSA and sectoral/national aggregates from the World Bank (2016).

4. Agricultural labor markets in Ethiopia

In this section we first describe the importance of wage income in total income and then the contribution of hired-in labor in total agricultural labor. Then, we discuss the associates of hired-in labor use in agriculture and of agricultural wage receipts.

4.1 Importance of agricultural wage income

Table 1 summarizes the data from the AGP baseline survey on the proportion of households engaged in different income generating activities and the importance of the income sources.\(^{12}\) Three major findings come from the table.

First, the share of off-farm income in Ethiopia is low relative to similar settings (Reardon et al., 2007) and it is mostly related to the agricultural sector. It is estimated that wage income
makes up 10 percent of total household income, which is about the same as the share of income from the livestock subsector. Crop income makes up 71 percent of total household income. About 89 percent of rural households’ income derives from the agricultural sector.

Second, 94 percent of the households were engaged in crop production and 22 percent in only crop production. Out of the 60 percent that derived income from livestock production, 59 percent relied also on crop production. About 21 percent of the households made some income from agricultural wage labor, and 25 percent earned some income from enterprise (non-agricultural) production.

(Table 1 around here)

Third, we see slight variation in the importance of income sources across regions. Crop income is relatively more important in Oromyia and SNNP regions and households in Tigray have relatively more diversified income sources. Agricultural wage income was highest in Amhara region, possibly linked to seasonal migration to cash crop - such as sesame - producing areas.¹³

We compare the summary in Table 1 with other recent large-scale datasets from rural Ethiopia. Overall, participation of households in different activities and shares of the income sources obtained from the Feed the Future impact evaluation dataset, collected in 2015, and the Ethiopian Rural Socioeconomic Survey dataset, collected in 2014, were of the same orders of magnitude. The latter datasets also suggest that the off-farm economy is overall small and that it is relatively more developed in the high potential agricultural areas covered in the AGP dataset.

We also compare the importance of the rural off-farm sector and rural wages with other countries. The contribution of off-farm income to total income in other African countries - see Reardon et al. (2007) - is twice higher relative to that in Ethiopia while off-farm income is even more important in Latin America and Asia. Moreover, average wage of agricultural workers in
areas covered in the AGP baseline survey was 19.5 birr (Ethiopian currency) or about 1.27 USD per day. Average wages of all rural workers, including non-agricultural labor, are slightly lower at 1.24 USD per day. These wages are considerably lower relative to wages in a number of Asian countries (see Wiggins and Keats (2014) and Zhang et al. (2014)). We find that average unskilled labor (daily) wages in AGP areas were 0.95, 1.59, and about 1 USD lower relative to those in Nepal, Bangladesh and Myanmar during similar periods.

4.2 Agricultural wage labor use

Table 2 summarizes the AGP baseline survey data on the type of labor that households relied on in crop production. Three important results can be summarized from the table. First, family labor is by far the most important contributor while hired labor accounts for only 7 percent of all agriculture work in the four major crop producing regions. Second, there is important regional heterogeneity in the share of hired-in labor: in Tigray it makes up 14 percent while it was lowest in Amhara at 4 percent. The relatively lower contribution of hired-in labor and higher contribution of wage income in Amhara possibly indicates the importance of seasonal migration to work on commercial farms. Third, the proportion of farms that exclusively rely on hired-in labor is low (only 1 percent). More than three-quarters of the households rely exclusively on family labor.\textsuperscript{14}

(Table 2 around here)

4.3 Associates of agricultural labor market use

We study the associates of households’ hired-in labor use in crop production using an empirical version of equation (12), which we specify as:

\[ L_h = \alpha_0 + \beta_1 X_h + \beta_2 Y_h + \beta_3 P_h + \beta_4 Z_h + e_h \]  

\text{(15)}
where h indexes households. \( L_h \) stands for the proportion of hired-in labor out of total labor used in crop production. P is a vector prices/values in households’ hired-in labor demand implied by the simple household model (equation (12)) and it includes zonal average agricultural wage, volume of output weighted average crop price, and household level income per worker earned from non-agricultural production. Equation (15) includes a number of other variables that are directly or indirectly associated with households’ demand for hired-in labor. Accordingly, X is a vector of five household demographic variables: gender, age, and education of household head, and household size, and dependency ratio (the ratio of number of household members under 15 and over 65 years of age to working members between 15 and 65). Y is a vector of variables that represent farm/farmer characteristics: Total cultivated area, Tropical livestock units, which normalizes the number of livestock households own in cattle units, and Land quality index. We account for farmers’ access to credit using a dummy variable and their exposure to modern production methods using a dummy which takes a value of 1 if the household head was selected as a model farmer in the 5 years preceding the survey, which is mostly bestowed on farmers that use modern inputs/methods. Z is a vector of location specific variables and \( e_j \) a random mean zero constant variance error term.

We employ a Tobit model on the AGP dataset to estimate equation (15). Results of the analyses are provided in Table 3. Estimates of crop price and wage are consistent with predictions of economic theory. Hired in labor is negatively associated with wages while it is positively related with crop prices. Households’ hired-in labor demand is positively associated with per worker income from non-agricultural production. This may result from labor shortages that arise as more family labor is used in non-agriculture where earning per worker is higher and/or due to the income effect of higher non-agricultural earnings per family worker.
Second, household characteristics are important for decisions on labor markets. The share of hired-in labor is associated negatively with household size and positively with dependency ratio. More labor is available for agricultural work in bigger households and a lower dependency ratio increases labor supply, ceteris paribus, both leading to a lesser use of hired-in labor. Households with educated heads rely more on hired labor likely because they have a higher likelihood to engage in alternative activities outside of their farms.  

Third, farm characteristics are also associated in an important way with households’ participation in agricultural labor markets. Farm size is positively but non-linearly associated with hired-in labor. Households that cultivate better quality land hire in relatively more labor, possibly because of the higher productivity of labor on better quality land. Moreover, hired-in labor use increases with the number of livestock households owned. This may result not only because more labor is needed to tend more livestock but also due to the positive effect on households’ income of owning a larger herd. Hired-in labor use is higher among households that accessed credit to purchase inputs and those selected as best performing, or model, farmers.

Fourth, hired-in labor use is influenced by location specific factors. Holding other factors constant, farmers in zones with a higher incidence of poverty hire in more labor, possibly because of the lower wage in such zones, which may have resulted from the higher wage labor supply. Hired-in labor use is higher in areas closer to local urban centers and to Addis Ababa. The latter is consistent with better functioning labor markets in areas closer to large population centers and with incentives for more intensive cultivation of land. Better functioning labor markets in areas closer to urban centers also imply employment opportunities, other than agriculture.
4.4 **Associates of agricultural wage receipts**

We employ the empirical version of equation (14) on the AGP baseline survey data to test if and to what extent agricultural wages are correlated with the agricultural task performed, worker characteristics, and locational factors. The linear regression equation we estimate is given as:

\[
\ln \text{Real wage}_j = \alpha_0 + \beta_1 X_j + \beta_2 Y_j + \beta_3 P_j P + \beta_4 Z_j + e_j
\]

(16)

where \( R_{eal\ wage_j} \) is PP-GCPI deflated real wages received by worker \( j \). \( X \) is a vector of dummy variables representing type of agricultural work performed. \( Y \) is a vector of variables representing worker characteristics, and \( Z \) is a vector of location specific factors. \( P \) stands for a vector that comprises per capita real value of zonal cereal/grains output, per capita real value of crop output sold, volume of output weighted average crop price, and poor-person’s non-food prices index. \( e_j \) is a random error term with zero mean and constant variance. We use ordinary least-squares (OLS) to estimate equation (16).

The results, which are provided in Table 4, indicate that, relative to land preparation, planting fetches lower wages while weeding and harvesting pay higher wages, ceteris paribus. The results also indicate that male workers are paid 9 percent higher than females.\(^{17}\) Moreover, wages of workers older than 50 are lower, possibly indicating that the productivity of elders is presumed to be lower.\(^{18}\)

Wage receipts of workers are positively affected by real per capita cereal output and the estimate is higher when using real per capita grain output, which, in addition to cereals, includes pulses and oilseeds. Consistent with equation (9) and with the positive association of hired-in labor demand and crop prices (Table 3), wages increase with weighted average price of crops in villages the households resided. Wages increase with real value of per capita crop sales, which may indicate that in more commercialized areas agricultural wages are higher. Non-food price
index is negatively and strongly associated with agricultural wages. This could work through the association of non-food prices with consumption, particularly with manufactured goods and leisure time, which in turn is associated with labor demand and wages.

(Table 4 around here)

Wages increase with proximity of center of the woreda (district) agricultural workers resided to Addis Ababa. Wages are also positively affected by proximity to market centers within or outside farmers’ villages. Agricultural wages are strongly negatively associated with the poverty head count index in the administrative zone even after controlling for other locational differences, indicating the strong link of agricultural wages with poverty measures. This may indicate the lower wages that result from the higher labor supply in areas where a higher proportion are poor. Region dummy variables imply that wages in Amhara, Oromiya, and SNNP are lower relative to wages in Tigray, where hired-in labor use is higher (Tables 2 and 3).

5. Rural wages

5.1 Trends

Understanding the patterns and trends in real wages of unskilled laborers in both rural and urban areas is important for at least three reasons. First, since rural wages mark the minimum wages for the manufacturing and service sectors, trends in rural-urban wage gaps over time will have important implications on Ethiopia’s effort to transform from largely agrarian towards a manufacturing-led economy. Second, rising wages have important implications given their impact on the cost of food production and consequently on food prices. An important question is whether future wage rises more than compensate for welfare losses due to subsequent price increases. Third, changes in rural wages often trigger changes in farming systems, driving for example the
The introduction of labor saving mechanization, or can bring about changes in farm sizes partly because the introduction of machines reduces the advantage of small-scale farm operations in labor supervision (Otsuka et al., 2014). We return to each of these points in section (5.3) after describing trends in real wages in this section and indicating some of the drivers of the observed changes in real wages in section 5.2.

The description in this section uses monthly data from CSA on daily wages of unskilled laborers covering the July 2004-September 2018 period. We first discuss trends in wages expressed in US dollars (USD) and US CPI deflated real USD. However, that deflation method might be imperfect because of changes in the overvaluation of the exchange rate over time (World Bank, 2014). We, therefore, rely also on two other deflators: regional general CPI (GCPI) from CSA (2016c) and poor persons’ general CPI (PP-GCPI) that we constructed in a manner described in Section 2.

Figure 1 depicts the daily wages of casual laborers expressed in USD and real USD. The graphs show what international investors would pay to employ unskilled labor in the country and they are therefore important indicators of the competitiveness of Ethiopia in labor-intensive industries. The figure shows that wages of unskilled laborers increased dramatically during the July 2004-September 2018 period. Specifically, wages per person per day expressed in USD and real USD, which averaged 0.86 and 0.92 in the third quarter of 2004 grew to nearly 3 and 2.5 in the third quarter of 2018, respectively. However, the growth was not consistent over this period and there was a slight decline in wages over the January 2009-September 2010 period. This might have been linked to the fast devaluation of the birr in that period (World Bank, 2014).

(Figure 1 around here)
To better evaluate changes in the purchasing power of agricultural wages, we depict regional average general CPI (GCPI) deflated real wages in Figure 2. The figure shows that GCPI deflated real wages increased considerably during the period, from 27.3 birr in the third quarter of 2004 to 45.5 birr in the third quarter of 2018 (a total growth of 54 percent) in rural areas. In urban areas, it increased from 28.4 to 48.3 birr (a total growth of 63 percent). Generally, the urban-rural wage gap has been low during the 2014-2018 period, when wages in urban areas were on average 5.5 percent higher. The urban-rural wage gap observed is considerably lower than those noted in other countries (Zhang et al., 2014; Yang et al., 2013). However, that gap has been widening in recent years. While urban and rural wages were at equal levels in the beginning of 2011, the wage gap stood at 6 percent in the third quarter of 2018.

(Figure 2 around here)

In Figure 3, we further provide daily real wages of unskilled labor deflated by the poor persons’ general CPI (PP-GCPI). PP-GCPI deflated average real wage of unskilled labor was 29.4 in rural areas and 31.5 birr in urban areas in the third quarter of 2004. This increased by nearly 16 birr and 15 birr in the third quarter of 2018. Similar with GCPI deflated wages the PP-GCPI deflated urban-rural real wage gap was higher during 2008-2009 in which it averaged 11 percent whereas the wage gap almost disappeared since. Growth in PP-GCPI deflated real wages were mostly similar with increases in GCPI deflated real wages indicating significant welfare improvements for such labor over time. However, the difference between PP-GCPI deflated urban and rural area real wages have in recent periods become smaller indicating higher prices of consumption goods in urban areas. We further note a significant decline in real wages during 2008 and between the middle of 2010 and 2011 when inflation rates were higher and wage adjustments were significantly lower (Headey et al., 2012).
The upshot of the discussion above is that wages, and purchasing power of wage laborers, have never been as high as at the end of the period studied. This in turn begs for investigating the factors that have been driving this growth as well as the implications of these wage changes. This is discussed in the next sections.

5.2 Drivers for change

The Ethiopian economy grew rapidly over the last decade and growth in agriculture has contributed considerably to the overall growth.\textsuperscript{19} We use the framework developed in section 3 to study in two ways how this rapid economic growth was associated with changes in real wages observed during the period. First, we use zonally aggregated CSA data that spans the 2004/5-2014/15 period to study whether real wages are associated with local economic growth and other zonal specific factors. Second, we investigate whether real rural wages are associated with aggregate GDP and valued added in agriculture, services, and manufacturing/industry sectors. We start the discussion by presenting results of two tests conducted to substantiate findings of the econometric analyses.

\textit{Stationarity and causality tests}

We test stationarity of variables used in the analyses to avoid misleading results that could arise if the variables are spuriously related because they are non-stationary or they appear to be related only because they have a common trend. We use routines in Stata to conduct the Levin-Lin-Chu, Im-Pesaran-Shin, and Fisher-type panel unit-root tests specified with and without linear trend. The null hypothesis of non-stationarity of poor-persons’ non-food price index (PP-NFCPI) was
not rejected by the Im-Pesaran-Shin (without trend) and Fisher-type methods. The null hypothesis was rejected by all methods and specifications in the remaining six variables except by the Im-Pesaran-Shin method (without trend) for real wages, and (with trend) for real cereals, grains, and manufacturing output per capita; and by the Levin-Lin-Chu method (without trend) for per capita manufacturing output. Given these results we assume associations of wages and the explanatory variables implied by results of the analyses are not spurious.

We also test whether there exists - and the direction of - causality between real wages and the explanatory variables. The tests are conducted using a user-written Stata code gwke82 (Dicle and Levendis, 2013). The results indicate that the null hypothesis that wage does not Granger cause all explanatory variables is not rejected by the dataset used. This excludes PP-NFCPI, which has causality that runs in both directions. Moreover, the null hypothesis that per capita value of cereal and grains output, crop price, and travel time do not Granger cause wages is rejected. These results suggest that relationships between real wages and all explanatory variables, except PP-NFCPI, are more than just associations.

Drivers of wage increases

(a) Zonal analyses

To study the relationship between zonal average real wages and local economic factors we estimate the following empirical equation:

\[
\ln \text{Real wage}_{jt} = \alpha_0 + \beta_1 P_{jt} + \beta_2 Z_{jt} + \delta_j \eta_j + \gamma_t \tau_t + \epsilon_{jt} \tag{17}
\]

In equation (17) \(j\) indexes rural administrative zones where \(j \in [1, 2, \ldots, 33]\) and \(t\) represents the 11 year period between 2004/5 and 2014/15. \(\text{Real wage}_{jt}\) stands for PP-GCPI deflated real wages. \(P_{jt}\) is a vector comprising regional real per capita manufacturing income and four zone level
variables: real per capita cereals/grains output, real per capita crop sales, volume of output weighted real crop price, and poor-person’s non-food CPI. \( Z_{jt} \) is a vector of two time-varying zonal specific variables while \( \eta_j \) are time invariant zonal fixed effects. \( \tau_t \) stands for a vector of year dummies while \( e_{jt} \) is the random error term with zero mean and constant variance. We use the fixed effects estimator to conduct the analyses.

The results provided in Table 5 indicate that with an elasticity of 10.6 percent, real per capita cereals output positively affect real wages and the elasticity is slightly higher (11.5 percent) when grains, a larger group of crops, are considered. We also use per capita crop sales to investigate the association between rural wages and commercialization in agriculture. The elasticity of real wages with respect to real per capita crop output sold is small at about 1.5, which is about a third of the elasticity with respect to real manufacturing output per capita.

(Table 5 around here)

Unlike in the high potential AGP zones, wages and weighted average crop prices are not statistically significantly related. Non-food price index is negatively associated with wages and has the highest elasticity, and is close in value to the analyses using the AGP dataset (presented in section 4). Real wages increase with proximity to urban centers of 50,000 or more population. Wages increase also with the proportion of zonal population covered by the Productive Safety Net Program (PSNP) although the magnitude is small. For a 100 percent increase in the population covered by PSNP real wages increase by less than 1 percent.

\( (b) \) Aggregate analyses

We further study the relationship between real wages and aggregate and sectoral GDP using the equation:
\[ \ln \text{Real wage}_t = \beta_0 + \beta_1 \ln y_t + e_t \]  
(18)

where \( y_t \) stands for real per capita GDP or real per capita value added in agriculture, services, and manufacturing/industry (World Bank, 2016). \( \text{Real wage}_t \) stands for PP-GCPI deflated nationally averaged real wages in rural areas in year \( t \), where \( t \in [1999, ..., 2014] \) and where zones are categorized as rural using the two criteria given in the second row of Table 6, where we provide results of the analyses.

Each entry in Table 6 is obtained by regressing the explanatory variables listed in the first column on real rural wages. The results indicate that rural wages increase at 28 and 36 percent for an increase in per capita GDP and agricultural value added, respectively, in predominantly rural zones, where an average woreda has a population of less than 30,000.\(^{21}\) Elasticity of wages with respect to aggregate and sectoral income is lower when woredas with 30,000-50,000 population are included in the analyses and the elasticities continue declining as woredas of increasingly larger population are included into the category of rural areas.

(Table 6 around here)

Two observations are notable about the results in Table 6. First, the elasticity of real wages with respect to agricultural value added is higher relative to value added in other sectors. This is likely given that in these rural zones most (over 94 percent, Table 1) derive a large proportion of (nearly 90 percent) their income directly from agriculture. Second, despite the value added in agriculture accounting for less than 50 percent of the GDP during the period analyzed, the elasticity of real rural wages with respect to aggregate GDP, is close but less than the elasticity of agricultural GDP, particularly in predominantly rural areas. The latter means that wages in rural areas respond most to changes in locally produced output, seemingly as most of the local population is engaged in these activities.
5.3 Implications of wage changes

In this section we discuss some of the likely implications of trends in rural wages observed in the sections above. In particular, we discuss the link between agricultural wages on the one hand, and rural poverty, adjustments in agricultural production practices, such as labor-saving modern inputs, agricultural mechanization, and increases in the likelihood of using of modern inputs due to alleviated seasonal liquidity constraints, on the other.

First, an important implication of increase in rural wages is its possible role in poverty reduction (Ravallion, 2000). We investigate this relationship first using Figure 4, which plots a quadratic function of the poverty Head Count Index (HCI) against real wages, both of which are zonally aggregated and pertain to years on which poverty HCI data is available: 1996, 2000, 2005, and 2011. The figure demonstrates that real wages are negatively correlated with poverty HCI. This relationship is particularly strong in areas with high poverty HCI. Similar patterns have been observed in other settings, e.g., Ravallion (2000).

(Figure 4 around here)

We also use the same data to econometrically test whether zonal poverty HCI is related with wage levels following Lanjouw and Murgai (2009). The general equation we estimate is given as:

\[
\ln Poverty\ HCI_{j,t} = \beta_0 + \beta_1 \ln Real\ wage_{j,t} + \eta_j + \tau + e_{j,t}
\]  

(19)

where \( Poverty\ HCI_{j,t} \) stands for poverty HCI of zone j in year t, such that \( j \in [1, 2, \ldots, 56] \) and \( t \in [1996, 2000, 2005, 2011] \); \( \eta_j \) represents zonal fixed effects; and \( \tau \) stands for a time trend variable. We estimate equation (19) using fixed-effects (FE) and OLS estimators whereby in the OLS specification \( \eta_j \) are either replaced by region dummies or dropped. Results of the analyses provided in Table 7 indicate that the elasticity of poverty HCI with respect to real wages is
negative and significant in all specifications. Moreover, elasticities from the OLS and FE specifications are close to each other. Elasticities from specifications that include a time trend range between -44 and -57 percent and those without time trends are unit elastic.

(Table 7 around here)

Second, we note increasing substitution of labor with labor-saving modern inputs such as herbicides over time in Ethiopia (Bachewe et al., 2015; Minten et al., 2016). Tamru et al. (2017) show that the adoption of herbicides by Ethiopian smallholders has grown rapidly, with application on cereals doubling to more than a quarter of the area under cereals between 2004 and 2014. They further show that weeding efforts are significantly lower when herbicides are used, indicating substitution between agricultural labor and herbicides and that the likelihood of herbicides adoption is strongly negatively associated with wages rates. These findings may imply that the particularly strong uptake of herbicides seen in commercially-oriented and well-connected farming areas may possibly be linked to the higher wages in such areas.

Third, higher rural wages often provide incentives for mechanization in agriculture (Binswanger 1986; Diao et al. 2014; Yang et al. 2013). Most surveys in Ethiopia do not collect data on mechanization, so we cannot assess the extent to which mechanization is used in different parts of the agricultural production process. In a rare exception, Berhane et al. (2015, 2017) analyze the use of mechanized farming services in crop production. They find that about 9 percent of smallholder crop producers used machinery services at some period during the agricultural season, mostly for plowing (5 percent) and relatively less for harvesting (3 percent) and threshing (2 percent). While adoption is still relatively low, Berhane et al. (2015) show a strong threshold effect in the use of mechanized services and agricultural wages in the community (Figure 5).

(Figure 5 around here)
While a slight upward trend is seen in the use of mechanization by smallholders for wage-levels up to 100 birr per day (just over 5 USD), use of mechanized services considerably expand after that wage threshold. However, it should be noted that most areas in Ethiopia are still far away from that wage threshold. Yang et al. (2013) found similar strong effects of wage increases on the adoption of mechanization in agriculture in China.

Fourth, other studies show that off-farm income might lead to improved agricultural practices by relaxing farmers’ financial constraints. Reardon et al. (1994) and Lamb (2004) show that such off-farm income sources might lead to significant farm investments and to a higher use of modern inputs, leading to higher agricultural productivity. We use the AGP baseline survey data to test the extent to which households’ level of off-farm income in Ethiopia is associated with the adoption of fertilizer, improved seeds, and agro-chemicals. Our results (non-reported) reveal that off-farm income is positively associated with a higher likelihood of adopting chemical fertilizers and improved seeds.

6. Conclusions

As economies develop and shift away from agrarian subsistence to commercial agriculture and increasingly to non-agricultural economic activities, labor markets increasingly become important in providing livelihoods for many people. At initial stages of this growth, and especially so in rural areas, these labor markets are important for poverty reduction as well as for assuring employment for the rural youth, an increasing concern in Africa, given its rapidly growing population and its ‘youth bulb’. However, these processes are not yet well understood, especially given the different growth trajectory that African economies are following (McMillan et al., 2014).
Ethiopia’s economy grew rapidly in the last decade, partly driven by rapid agricultural growth. However, priorities are shifting in the planning process and there is increasing emphasis on stimulating other sectors as sources of future economic growth (National Planning Commission, 2016). Given that such shifts will have important implications on labor markets, it is important to understand rural and agricultural labor markets in this context. This is especially important given a large majority of the Ethiopian population is still involved in agricultural/rural areas, as is the case in most of Africa. Our paper aims to fill this knowledge gap and contributes to greater understanding of rural wages and agricultural labor markets in these settings.

We find that off-farm income makes up almost 18 percent of household income. Wage income, which accounts for 10 percent, is estimated to be about as important as livestock income. We further estimate that only 7 percent of the agricultural production is carried out by hired labor. We also find that there is considerable heterogeneity in rural unskilled labor markets over space and time. Agricultural labor markets are relatively much more important in better connected areas and in urban areas, which is also reflected in higher wages in these areas. This suggests that connectedness and urbanization are among the driving forces towards improved labor markets.

While wages of unskilled labor in rural areas of Ethiopia are still low relative to the international context, real wages are on the rise, measured both in US dollars and real birr. This is shown to be seemingly driven by an improvement in agricultural performance, which also leads to a reduction in poverty. This development in labor markets has been found to lead to an increasing adoption of labor-saving technologies in agriculture, such as mechanized services – though starting from a low base – as well as to a more widespread use of herbicides that save on weeding labor.

These findings have important implications on policy. First, low wages have been an asset for attracting investors to Ethiopia, and they have contributed to the success of investments in labor-intensive industries, such as floriculture. However, our results indicate that Ethiopia may
gradually lose that edge. Ethiopia therefore needs to make sure that the skills of its young population are upgraded so that industries can develop in those areas where labor productivity is higher. Second, the higher costs of labor as well as the increasing commercialization of agriculture will require increasing adoption of labor-saving technologies in the sector. It is therefore important that Ethiopia proactively implements policies that allow for the provision of such appropriate technologies at low cost. Third, flexible and responsive labor markets require easier migration to areas with employment opportunities. Therefore migration needs to be encouraged through more flexible land tenure and more secure land rental rules. Such policies could also facilitate the consolidation of small farms, given the introduction of labor-saving technologies. Furthermore, this may subsequently reduce the incentives to operate small farms which have the traditional advantages over larger farms of lower costs of labor supervision.
References


### Tables

#### Table 1
Importance of off-farm income in rural areas

<table>
<thead>
<tr>
<th>Income source</th>
<th>All regions</th>
<th>Tigray</th>
<th>Amhara</th>
<th>Oromiya</th>
<th>SNNP</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Contribution of source to total income (%)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Crop</td>
<td>71.4</td>
<td>59.8</td>
<td>69.6</td>
<td>72.2</td>
<td>73.3</td>
</tr>
<tr>
<td>Livestock</td>
<td>10.7</td>
<td>13.7</td>
<td>13.6</td>
<td>10.1</td>
<td>8.3</td>
</tr>
<tr>
<td>Agricultural wage income</td>
<td>6.6</td>
<td>7.8</td>
<td>9.1</td>
<td>5.9</td>
<td>5.1</td>
</tr>
<tr>
<td>Non-agricultural wage income</td>
<td>3.1</td>
<td>9.4</td>
<td>2.4</td>
<td>3.5</td>
<td>2.5</td>
</tr>
<tr>
<td>Enterprise income</td>
<td>8.1</td>
<td>9.3</td>
<td>5.3</td>
<td>8.3</td>
<td>10.9</td>
</tr>
<tr>
<td><strong>Households earning some income by type (%)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Crop income</td>
<td>94.1</td>
<td>87.1</td>
<td>93.6</td>
<td>94.2</td>
<td>95.5</td>
</tr>
<tr>
<td>Livestock income</td>
<td>60.2</td>
<td>63.1</td>
<td>74.4</td>
<td>57.5</td>
<td>48.9</td>
</tr>
<tr>
<td>Agricultural wage income</td>
<td>21.4</td>
<td>16.3</td>
<td>29.0</td>
<td>20.2</td>
<td>15.9</td>
</tr>
<tr>
<td>Non-agricultural wage income</td>
<td>8.1</td>
<td>21.5</td>
<td>6.9</td>
<td>8.6</td>
<td>7.0</td>
</tr>
<tr>
<td>Enterprise income</td>
<td>25.4</td>
<td>20.2</td>
<td>18.0</td>
<td>28.8</td>
<td>28.1</td>
</tr>
</tbody>
</table>

Source: Authors’ computation using the AGP baseline survey data (2011).
Table 2

Hired labor use in crop production

<table>
<thead>
<tr>
<th>Region/crop type</th>
<th>Share of family labor (%)</th>
<th>Share of hired-in labor (%)</th>
<th>Households using only family labor (%)</th>
<th>Households using only hired labor (%)</th>
<th>Households using family and hired labor (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>All regions</td>
<td>93.0</td>
<td>7.0</td>
<td>76.1</td>
<td>1.1</td>
<td>22.8</td>
</tr>
<tr>
<td>Tigray</td>
<td>86.1</td>
<td>13.9</td>
<td>62.2</td>
<td>3.5</td>
<td>34.3</td>
</tr>
<tr>
<td>Amhara</td>
<td>96.1</td>
<td>3.9</td>
<td>81.4</td>
<td>0.3</td>
<td>18.3</td>
</tr>
<tr>
<td>Oromiya</td>
<td>93.0</td>
<td>7.0</td>
<td>72.5</td>
<td>0.4</td>
<td>27.1</td>
</tr>
<tr>
<td>SNNP</td>
<td>90.6</td>
<td>9.4</td>
<td>78.8</td>
<td>3.0</td>
<td>18.2</td>
</tr>
</tbody>
</table>

Source: Authors’ computation using the AGP baseline survey dataset (2011).
### Table 3

** Associates of hired-in labor use  

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>SE</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent variable: share of hired-in labor in percent</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Household characteristics</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gender of household head (=1 if male)</td>
<td>-8.343***</td>
<td>2.115</td>
</tr>
<tr>
<td>Age of household head (years)</td>
<td>-0.080</td>
<td>0.061</td>
</tr>
<tr>
<td>Education of household head</td>
<td>5.242***</td>
<td>0.828</td>
</tr>
<tr>
<td>Dependency ratio</td>
<td>0.173***</td>
<td>0.039</td>
</tr>
<tr>
<td>Household size</td>
<td>-3.698***</td>
<td>0.483</td>
</tr>
<tr>
<td><strong>Farm characteristics</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cultivated area (hectares)</td>
<td>12.175***</td>
<td>1.083</td>
</tr>
<tr>
<td>Cultivated area-squared</td>
<td>-0.686***</td>
<td>0.100</td>
</tr>
<tr>
<td>Land quality index</td>
<td>1.747***</td>
<td>0.431</td>
</tr>
<tr>
<td>Tropical livestock units</td>
<td>1.318***</td>
<td>0.222</td>
</tr>
<tr>
<td>Accessed credit? (=1 if yes)</td>
<td>4.848**</td>
<td>2.251</td>
</tr>
<tr>
<td>Selected as model farmer? (=1 if yes)</td>
<td>8.153**</td>
<td>3.253</td>
</tr>
<tr>
<td><strong>Prices/Income</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Agricultural wages</td>
<td>-0.496***</td>
<td>0.101</td>
</tr>
<tr>
<td>Crop price</td>
<td>1.176***</td>
<td>0.304</td>
</tr>
<tr>
<td>Non-agricultural income per worker (00 birr)</td>
<td>0.156***</td>
<td>0.041</td>
</tr>
<tr>
<td><strong>Location</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Travel time to nearest 50K town (mns)</td>
<td>-0.022***</td>
<td>0.006</td>
</tr>
<tr>
<td>Distance from Addis (00 kms)</td>
<td>-5.871***</td>
<td>0.971</td>
</tr>
<tr>
<td>Zonal poverty HCI</td>
<td>0.165**</td>
<td>0.073</td>
</tr>
<tr>
<td>Amhara</td>
<td>-36.68***</td>
<td>3.637</td>
</tr>
<tr>
<td>Oromiya</td>
<td>-49.62***</td>
<td>4.284</td>
</tr>
<tr>
<td>SNNP</td>
<td>-30.68***</td>
<td>3.649</td>
</tr>
<tr>
<td>Constant</td>
<td>-8.947</td>
<td>7.863</td>
</tr>
<tr>
<td>Sigma</td>
<td>55.66***</td>
<td>1.054</td>
</tr>
<tr>
<td><strong>Source:</strong> Authors’ analysis.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>*<em>Coefficients with superscripts <em><strong>,</strong>, and * are significant at 1, 5, and 10 percent levels, respectively.</em></em></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
### Table 4
Associates of rural wage receipts

<table>
<thead>
<tr>
<th>Variable</th>
<th>Dependent variable: log of real agricultural wages (birr/day)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
</tr>
<tr>
<td><strong>Type of work (land preparation is omitted)</strong></td>
<td></td>
</tr>
<tr>
<td>Planting</td>
<td>-0.143***</td>
</tr>
<tr>
<td>Weeding</td>
<td>0.125***</td>
</tr>
<tr>
<td>Harvesting</td>
<td>0.162***</td>
</tr>
<tr>
<td>Herding</td>
<td>-0.036</td>
</tr>
<tr>
<td><strong>Worker characteristics</strong></td>
<td></td>
</tr>
<tr>
<td>Gender of worker (=1 if male)</td>
<td>0.089***</td>
</tr>
<tr>
<td>Worker is older than 50 (=1 if yes)</td>
<td>-0.095**</td>
</tr>
<tr>
<td>Education</td>
<td>0.015</td>
</tr>
<tr>
<td><strong>Prices/value</strong></td>
<td></td>
</tr>
<tr>
<td>Value of cereals output per capita</td>
<td>0.169***</td>
</tr>
<tr>
<td>Value of grains output per capita</td>
<td>0.112*</td>
</tr>
<tr>
<td>Average crop price, volume of output weighted</td>
<td>0.219***</td>
</tr>
<tr>
<td>Poor-persons' non-food CPI</td>
<td>-0.424***</td>
</tr>
<tr>
<td><strong>Location</strong></td>
<td></td>
</tr>
<tr>
<td>Distance to daily/periodic market (kms)</td>
<td>-0.011***</td>
</tr>
<tr>
<td>Distance from Addis (00 kms)</td>
<td>-0.325***</td>
</tr>
<tr>
<td>Zonal poverty head-count index</td>
<td>-0.337***</td>
</tr>
<tr>
<td>Amhara</td>
<td>-0.169**</td>
</tr>
<tr>
<td>Oromiya</td>
<td>-0.722***</td>
</tr>
<tr>
<td>SNNP</td>
<td>-0.277***</td>
</tr>
<tr>
<td>Constant</td>
<td>4.026***</td>
</tr>
<tr>
<td>F-statistics</td>
<td>32.67</td>
</tr>
<tr>
<td>Number of observations</td>
<td>2,296</td>
</tr>
</tbody>
</table>

Source: Authors’ analysis

Coefficients with superscripts ***, **, and * are significant at 1, 5, and 10 percent levels, respectively.
Table 5
Estimates of unskilled labor wage elasticity (2004/5-2014/15)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient (SE)</th>
<th>Coefficient (SE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value of cereals output per capita</td>
<td>0.106* (0.058)</td>
<td></td>
</tr>
<tr>
<td>Value of grains output per capita</td>
<td>0.115* (0.061)</td>
<td></td>
</tr>
<tr>
<td>Value of crop sales per capita</td>
<td>0.015*** (0.005)</td>
<td>0.014*** (0.005)</td>
</tr>
<tr>
<td>Manufacturing output per capita (regional)</td>
<td>0.044** (0.019)</td>
<td>0.042** (0.019)</td>
</tr>
<tr>
<td>Crop price (volume of output weighted)</td>
<td>-0.044 (0.050)</td>
<td>-0.046 (0.050)</td>
</tr>
<tr>
<td>Poor-persons' non-food CPI</td>
<td>-0.401*** (0.081)</td>
<td>-0.391*** (0.082)</td>
</tr>
<tr>
<td>Population covered by Productive Safety Net Program (%)</td>
<td>0.007** (0.003)</td>
<td>0.007** (0.003)</td>
</tr>
<tr>
<td>Travel time to nearest 50K town (hours)</td>
<td>-0.011* (0.006)</td>
<td>-0.011* (0.006)</td>
</tr>
<tr>
<td>Zonal fixed effects</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Period dummies</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Constant</td>
<td>4.478*** (0.554)</td>
<td>4.375*** (0.586)</td>
</tr>
<tr>
<td>F-statistics</td>
<td>14.19</td>
<td>14.21</td>
</tr>
<tr>
<td>Number of observations</td>
<td>336</td>
<td></td>
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</table>

Source: Authors’ analysis
Coefficients with superscripts ***, **, and * are significant at 1, 5, and 10 percent levels, respectively.
### Table 6

<table>
<thead>
<tr>
<th>Explanatory variable</th>
<th>Dependent variable: real wages in rural areas where rural areas are defined as:</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Average woreda population in zone &lt;30K</td>
</tr>
<tr>
<td>Real GDP</td>
<td>0.276***</td>
</tr>
<tr>
<td>Real agricultural GDP</td>
<td>0.355***</td>
</tr>
<tr>
<td>Real industry GDP</td>
<td>0.226***</td>
</tr>
<tr>
<td>Real manufacturing GDP</td>
<td>0.251***</td>
</tr>
<tr>
<td>Real services GDP</td>
<td>0.195***</td>
</tr>
</tbody>
</table>

Source: Authors’ analysis.

Coefficients with ***, **, and * are significant at 1, 5, and 10 percent levels, respectively.
Table 7
Association of poverty head count index and real wages

<table>
<thead>
<tr>
<th>Variable</th>
<th>Dependent variable: log of poverty HCI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS, including</td>
</tr>
<tr>
<td></td>
<td>Region dummies and time trend</td>
</tr>
<tr>
<td>Log of real wages</td>
<td>-0.574***</td>
</tr>
<tr>
<td></td>
<td>(0.179)</td>
</tr>
<tr>
<td>Constant</td>
<td>6.027***</td>
</tr>
<tr>
<td></td>
<td>(0.615)</td>
</tr>
<tr>
<td>F statistics</td>
<td>8.4</td>
</tr>
<tr>
<td>Number of observations</td>
<td>211</td>
</tr>
</tbody>
</table>

Source: Authors’ analyses.
Coefficients with superscripts ***, **, and * are significant at 1, 5, and 10 percent levels, respectively.
Figures

Figure 1
Wages of unskilled laborers per day in USD and real USD

![Graph showing wages in USD and US CPI deflated real USD]


Figure 2
Trends in daily wages of unskilled laborers in rural and urban areas

![Graph showing trends in real wages in December 2011 prices]

Source: Authors’ computation using CSA nominal wages data (2015a) and CSA regional GCPI data (2015b)
Figure 3
Poor persons’ general CPI (PP-GCPI) deflated real wages of unskilled laborers

Source: Authors’ computation using nominal wages data from CSA (2015a)

Figure 4
Correlation of real wages and poverty head count index

Source: Authors’ analyses.
Figure 5
Mechanization and daily wage rates

Source: Berhane et al. (2015)
Note: Local polynomial regression. The shaded area represents the 95-percent confidence interval.
The vertical axis measures the share of farmers who are using machines to plough, thresh or harvest.
Endnotes

1 Previous studies that looked at this issue were based on relatively small surveys and/or are outdated (Holden et al., 2004; Dercon and Krishnan, 1996; Block and Webb, 2001).

2 In the first 15 days of each month in the European Calendar three observations on prices of goods and services are made by interviewing three consumers and/or retailers while data on wages are collected by interviewing three hiring households and/or workers. The prices reported by these sources may vary depending on, among others, the extent of negotiations, by type of good/service, and by type of customer. However, the three price/wage observations show strong correlation. We use a simple average of the three observations since the dataset has no information on these details.

3 The expenditure shares are regional averages and given for urban and rural areas separately. So, we compute the indices separately for rural and urban woredas. We use CSA’s population census of 2007 (CSA, 2009d) to categorize a woreda as urban if its population is 50,000 or higher.

4 The producer price dataset covers 617 of the 734 woredas in Ethiopia.

5 The reports, which can be downloaded from www.csa.gov.et, provide further details on data collection methods.

6 Data on crop utilization/sales is available for 2008 to 2014. We compute the proportion for 2004-2007 assuming that the average annual change in proportion of crop output sold during 2008-2014 also held during 2004-2007.

7 Currently, the AGP excludes only Addis Ababa and the predominantly pastoral regions of Afar and Somali.

8 For further details on sampling design and other related issues see also Berhane et al. (2013).

9 The four regions represent most of the country’s sedentary agriculture. In 2010/11 these regions together accounted for 96 percent of the number of rural households engaged in mixed crop-livestock agriculture, 97.3 percent of the nationwide cultivated area, and 96.3 percent of total crop output, (CSA, 2011a). The number of households covered in the AGP baseline survey represented 65.3 percent of the nationwide total in 2010/11.

10 This may arise, for instance, due to specialization of labor, monitoring and transaction costs associated with using hired-in labor, and imperfect rural labor markets (Strauss, 1986). Moreover, the AGP baseline dataset indicates that out of the households that hired-in agricultural labor 17 percent also hired-out agricultural labor (or 5 percent of all households both hired-in and hired-out agricultural labor).

11 E is used as a proxy for marginal value of product of family labor to control for the effect of labor use decisions in non-agricultural production on agricultural and hired-out labor use.

12 In this study we focus on agricultural wage labor, which we view as distinct from other rural wage labor and business activities, thereby eliminating discrepancies that may arise due to differences in definitions of rural and agricultural.

13 We use Herfindahl’s income diversification index (HDI), which accounts for both the number and importance of income sources, to test if there exist regional differences in income diversification. The HDI is computed for each household h as: $HDI_h = 1 - \sum_{k=1}^{5} (\frac{1}{\sum_{k=1}^{5} Y_{hk}})^2$ whereby the term in parentheses is the share of income source k, (Y_{hk}), in total income ($\sum_{k=1}^{5} Y_{hk}$), where $k \in [1, 2, \ldots, 5]$. The value of HDI increases with diversification and approaches to 1 as the share of each income sources approaches to 1/5. Accordingly, average HDI is the highest in Tigray (0.35) followed by Amhara (0.29) while average HDI in Oromiya (0.273) and SNNP (0.266) were about the same. All differences in regional average HDI, except that between Oromia and SNNP, were statistically significantly different from zero at conventional levels of significance.
Further disaggregating the data across crop types also reveals surprisingly little differences in hired-in labor use across crops. Hired-in labor use ranged from 4.5 percent for pulses to 7.5 percent for oilseeds.

Land quality index is computed by multiplying perceived soil fertility (1=infertile, 2=semi-fertile, 3=fertile) and slope of land (1=steep, 2=gentle, 3=flat). The index, therefore, ranges from 1 to 9, varying from the poorest to the best land quality.

The AGP dataset indicates that out of illiterate household heads 13 percent are not fully engaged in farming while this proportion is 5 percent among heads educated in grades 1-3 and 4-8. Over a quarter of heads educated in grades 9 or higher have non-agricultural major occupations.

Note that all continuous variables are in logs. Note also that elasticity of wages, $W$, with respect to a dummy variable, $X$, is given by $E_{WX} = \exp(\beta_X) - 1$, where $\beta_X$ is the estimate of $X$ (Halvorsen and Palmquist, 1980).

We use a dummy variable to represent age because graphing wages against age clearly indicates that wages decline after a certain threshold age. Analyses that use age in years provide an insignificant estimate for the variable while estimates of other variables are almost identical to those in Table 4.

Growth in real gross domestic product (GDP) averaged 11 percent during 2004/05-2014/15 and agriculture, which grew at 7.6 percent per annum during the same period, on average accounted for a third of the GDP growth (World Bank, 2015).

Service sector outputs are not included in the analysis because disaggregated data is unavailable.

Regressing real rural wages in the AGP and CSA datasets only on per capita grains output and region and zonal dummies provided elasticities of 32 and 28 percent, respectively, which are close to that obtained from the aggregate analysis.