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Urban Wage Behavior and Food Price Inflation: The Case of Ethiopia

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Abstract

On the back of both a global food crisis and various domestic factors, Ethiopia has experienced one of the world's fastest rates of food inflation in recent years. Yet the lack of high frequency survey data means that very little is known about the welfare impacts of these price changes. This study attempts to fill that knowledge gap using a unique monthly series of casual wages from 119 locations in both Ethiopian cities and rural towns. We use this data for two types of analysis. First, we construct a set of "poor person's price indices" which we then use to deflate the daily laborer wage series in an effort to gauge the welfare trends among the urban poor. Second, we conduct formal econometric tests of whether changes in nominal wages respond to changes in food and non-food prices. We find alarming results. The disposable income of daily laborer's declined sharply as food prices soared in 2007–2008, and there is neither descriptive nor econometric evidence that wages substantially adjust to higher food prices, except in the long run.

Keywords: poverty, inflation, urban Ethiopia, casual wages

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1. Introduction

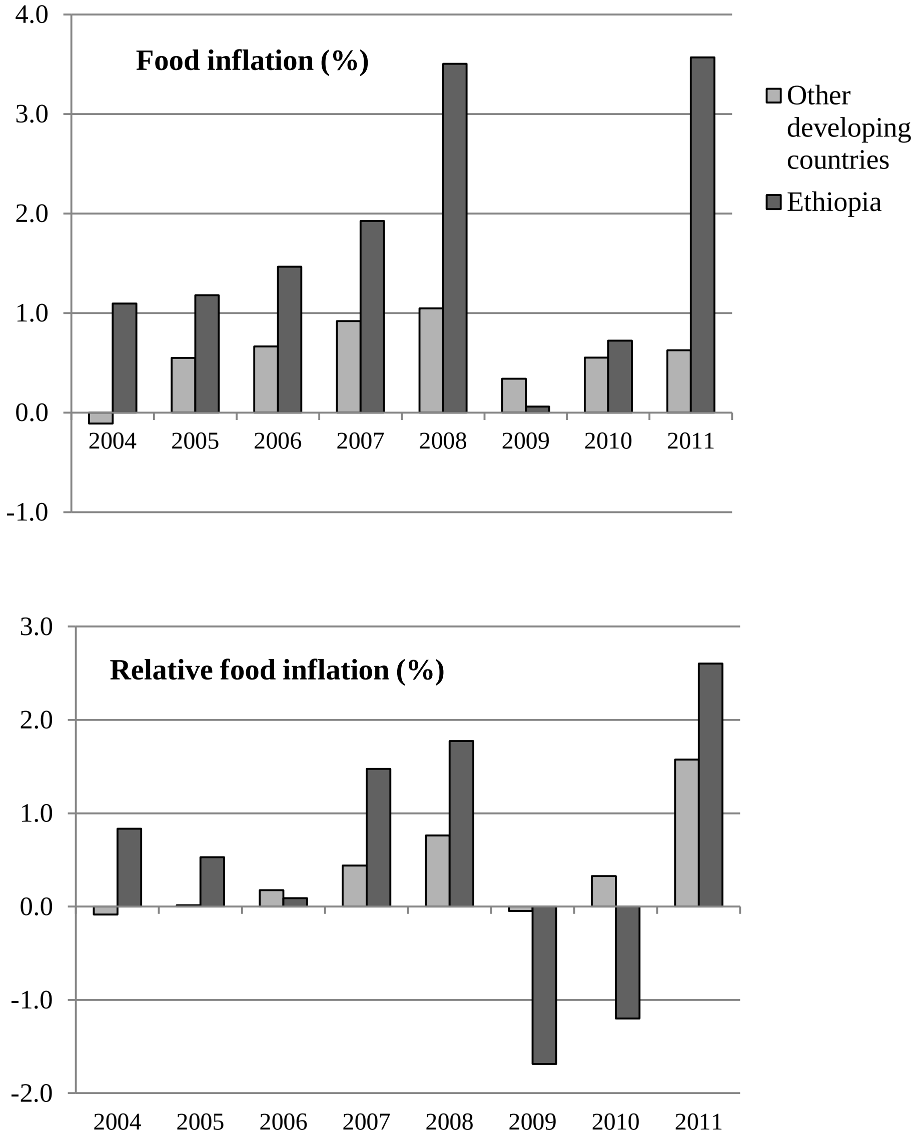
In recent years there has been greatly renewed interest in gauging the effect of higher food prices on poverty. The international food price spikes of 2007–2008 and 2010–2011 saw the international prices of some staple foods—such as wheat, maize, and rice—double or even triple in the space of a few months. At the same time several in-depth analyses of food price trends in developing countries have identified huge variation in the extent of the transmission of international prices into domestic markets (Headey and Fan 2010; Minot 2011; Dawe 2008), and in the welfare impacts of higher food prices (Dessus, Herrera, and de Hoyos 2008; Ivanic and Martin 2008; Ivanic, Martin, and Zaman 2011; Headey 2012). In terms of both price transmission and welfare impacts it appears that many African countries were the worst affected by the crisis.

In this paper we look at the welfare impacts of rapid food price inflation in the cities and large rural towns of Ethiopia, a country for which there is a sizeable and important knowledge gap on this issue. In 2008, Ethiopia had the highest rate of month-on-month food inflation rate in the developing world, at 3.5 percent per month (Figure 1.1). Most of this food inflation was driven by higher staple food prices, such as maize, wheat, and *teff*. Being an extremely poor country and typically one the largest food aid recipients in the world, such high rates of food price inflation have naturally raised concerns about the impacts of higher food prices on Ethiopia's poor.

Existing research has therefore explored this important question, yet faced important data constraints. In rural areas lack of income data in the 2004/05 national household survey prevent the identification of net food consumption, although Ticci (2011) makes a valiant effort using 1999/2000 income data. Under some assumptions she finds that the rural poor are better off, but under other assumptions they are worse off. In urban areas the standard expectation is that the urban poor are quite adversely affected by higher food prices since they are almost solely net food consumers. Ticci (2011) simulated a 12.6 point increase in urban headcount poverty using the 2004/05 national survey. Alem and Söderbom (2012) used the smaller Ethiopian Urban Household Survey panel data from 2008 and 2004. They find that that 87 percent of urban households in 2008 reported higher food prices as the largest economic shock faced in recent years. And while their study says little about the magnitude of the shock in quantitative terms, their data do suggest that urban households with casual workers saw the lowest consumption growth over this period[1].

[1] Other research in the Ethiopian context has focused on determinants of inflation and price transmission, though we do not review this separate literature here. See Ulimwengu, Workneh, and Paulos (2009) for an example.

Figure 1.1—Average monthly inflation in Ethiopia and other developing countries: 2004–2011



Source: ILO (2012)
Notes: Food inflation is measured as the average month-on-month change over a calendar year. Relative food inflation is the changes in the ratio of the food consumer price index (CPI) to the non-food CPI, also for month-on-month inflation. The average inflation for "Other developing countries" includes only those countries that are relatively poor, with food budget shares 50 percent or greater. This is to ensure greater comparability to Ethiopia.

In addition to the lack of income data, all of these existing works use low frequency data (although Alem and Söderbom (2012) are at least fortunate in having one round of data from the 2008 food crisis). Infrequent household surveys therefore yield either occasional snapshots or simulated welfare impacts. This has two limitations. First, such results effectively abstract from the time dimension of food price changes. A fall in income that persists for one month should obviously not be equated to a fall in income that persists for one year. Second, simulation approaches typically abstract from the possibility of income/wage growth, including wage adjustment to higher food prices.[2] In other words, the

[2] Ivanic and Martin (2008) use the econometric results of Ravallion (1990) to induce some wage adjustments in their model. In subsequent simulations, however, wage adjustments were excluded.

simulation approaches of Ticci (2011) and Dessus, Herrera, and de Hoyos (2008) both use 2004/05 or 1999/2000 survey data, and then shock the model with real food price changes, but not with any other sources of income change. While the partial impact of food prices on poverty is in many regards still a relevant issue, partial effects are arguably less policy relevant in economies experiencing very high economic growth (Headey 2012), such as Ethiopia in the 2000s.

In view of these limitations, this paper explores the impact of higher food prices using an unusually rich high frequency (monthly) data set on consumer prices and informal/unskilled wages. We use this data to inform two important questions. First, how have predominantly poor (and predominantly urban) casual laborers been affected by higher food prices over the last decade in Ethiopia? And second, is there any evidence that casual laborer wages adjusted to higher food prices?

We believe there are certainly some advantages to using wage data to gauge the impacts of higher food prices, at least for the urban areas and rural towns covered by our data. First, the urban poor derive the vast majority of their income from selling their labor, and very few get any sizeable income from producing food. Thus, we believe that the wage series used herein are a good proxy for the income of a substantial section of the urban poor. Indeed, Deaton and Dreze (2002) have argued that wages can often be a poverty indicator in their own right if they reflect the reservation wage of the very poor. A limitation is that we can say nothing about the rural poor, who still make up the bulk of Ethiopia's total poor. Our approach also falls short of factoring in various coping mechanisms, such as adjustments of expenditure patterns[3], working longer hours, or greater reliance of formal or informal social safety nets.

Second, as opposed to the snapshots provided by household surveys, high frequency data allow us to examine both secular welfare trends as well as the volatility of urban welfare. This is important because although Ethiopia has experienced tremendous price volatility in recent years (2007–2008 and 2010–2011), it has also experienced one of the most rapid economic growth rates in the world, with GDP growth averaging 11 percent per annum over 2005–2010.

Despite these advantages of wage data, the only analogous research we have uncovered on this topic is that of Mason et al. (2011), who look at urban manufacturing wages in Zambia and Kenya. These authors deflate these wage series by food price indices to see whether the food purchasing power was adversely affected by the global food crisis. They find that although real wages fell substantially during the 2008 crisis, strong wage growth prior to the crisis meant that urban wage earners where still relatively better off in 2008. While insightful, those authors acknowledge that manufacturing workers are not necessarily poor, and that informal wages could have trended quite differently. In contrast to their study, our data pertain to the wages of "daily laborers", which covers what are essentially informal or casual workers who are predominantly poor. Our data also have much richer spatial coverage, which would seem important in a country as vast, heterogeneous, and underdeveloped as Ethiopia. Moreover, rather than using an overall food price index, we use the consumer price data and 2004/05 household expenditure data to construct a set of poor person's food and non-food price indices for the urban areas of each of the different regions of Ethiopia. These indices should therefore provide a somewhat more accurate estimate of welfare trends.

On the second question of whether wages adjust to higher food prices in developing countries, the existing literature is vary sparse and seems solely to apply to the wages of

[3] The adjustment of expenditure patterns could include reducing non-food expenditures (such as delaying some purchases) or switching to cheaper sources of calories (for example, maize is a much cheaper source of calories than teff). Such adjustments could still imply a significant welfare loss. For example, lower expenditures on schooling or health expenditures, or working longer hours, should obviously be regarded as welfare losses. Similarly, the reduce of more nutrient-rich high value foods in favor of cheaper sources of calories has negative implications for both psychological utility and nutrition outcomes (e.g. Block et al. 2004).

agricultural laborers in Asia. Specifically, previous research has focused on the rice-dominated economies of Bangladesh and the Philippines where landlessness is quite high, such that agricultural laborers make up a significant share of the rural poor. In Bangladesh that research only uncovered wage adjustment over the long run (Ravallion 1990; Rashid 2002; Raiman 2009), but in the Philippines Lasco, Myers, and Bernsten (2008) recently found reasonably high agricultural wage adjustment even in the short run (albeit using annual data). We have seen no analogous study for unskilled urban workers. Moreover, the data used in these studies are relatively weak, covering a very limited number of markets with annual data. In contrast, our dataset comprises 119 urban and rural towns with monthly data, which should allow for much more precise estimates of any short run adjustments.[4] Moreover, much of the earlier work on this subject used now outdated econometric techniques to test for wage adjustment. We use more rigorous panel techniques, with additional tests for spatial heterogeneity in labor markets.

The remainder of this paper is structured as follows. In section 2 we provide a brief theoretical and contextual background to urban and rural town labor markets in Ethiopia in order to frame our hypotheses and expectations. In section 3 we describe the consumer price survey, the construction of poor person's price indices, and the econometric tests for wage adjustments. In section 4 we present our results on both trends in real wages and formal econometric tests of wage adjustment. Section 5 concludes.

2. Data and methods

2.1. CSA price and wage data

The price and wage data used in this study are based on monthly quotations collected as part of the Ethiopian Central Statistical Agency (CSA 2011b) *Consumer Price Survey*. This is the data used to calculate the official consumer price index (CPI) and its various components. The data were collected by CSA enumerators in 119 "markets" in all 11 regions of Ethiopia between July 2001 and October 2011. These markets certainly cover the major urban markets, but they also cover what are essentially large rural towns with populations of between 5,000 to 20,000 people (however, for the remainder of the paper we call all these markets "urban" unless otherwise noted). The number of markets in each region is also approximately proportional to the region's share of the total urban population, to ensure a sufficient degree of national representativeness. The full list of markets is given in Appendix A, but we note here that 32 markets are surveyed in Southern Nations, Nationalities, and Peoples (SNNP) region, 24 in Oromia, and 20 in Amhara (the three biggest regions), while 12 markets are surveyed in Addis Ababa (by far the largest urban center with around 3 million people). The smaller regions include only a handful of markets.

As for the data collection, CSA enumerators—who reside permanently in these markets—collect price and weight/volume data from traders, retailers, and consumers for around 400 items. For each item a maximum of three price quotations are collected from three different retailers/households, though enumerators are encouraged to survey the same retailers/households if possible. Among the list of consumer prices, monthly salaries of domestic maids, guards, and daily laborers are also obtained from three hiring households.

Whilst all three items are common sources of employment for the poor, for the purposes of this paper we elected not to analyze maids or guards' wages because these kinds of

[4] Indeed, it could be argued that annual data are incapable of providing insights on short run adjustments if the short is defined in months, not years.

household employees are often paid with food-in-kind (one implication being that household employees were partly protected from food inflation). In contrast, it is much less common to pay daily laborers in this fashion. Even so, the broad category of “daily laborers” covers a wide range of common employment types, particularly in the booming construction industry, but also many other types of largely manual labor. As an informal employment category, this wage series also seems broadly representative of the earnings of the urban poor. The CSA labor force survey (CSA 2011a) estimates that just under 40 percent of employment in Ethiopia is informal, and this definition does not even include private household employees such as guards and maids. About 40 percent of the urban population is also identified as poor according to the national poverty line, while about 20 percent of the urban population was classified as unemployed over the period in question.[5]

For these reasons we conclude that there is likely to be a high coincidence between casual employment, unemployment, and urban poverty, and therefore that this “daily laborer” wage series is a relatively good indicator of the income earnings of the urban poor. We also note that although the vast majority of Ethiopia’s poor are rural (since the total population is about 80 percent rural), official urban poverty rates in Ethiopia are almost as high as rural poverty.[6]

Another advantage of this data is its spatial coverage of 119 markets across all the regions of Ethiopia. While potential errors in data collection should make us wary of inferring too much from some of the smaller regions in which only a handful of markets are surveyed, the extensive spatial coverage of the CSA (2011b) survey affords us the opportunity to explore spatial heterogeneity in wage trends and wage–food price relationships. This is likely to be particularly important in Ethiopia given that most analysts still regard the Ethiopian labor market as quite segmented across space and occupational categories (World Bank 2007; Bigsten, Mengistae, and Shimeles 2007; Serneels 2008; Dendir 2006).

2.2. Construction of pro-poor price indices

Clearly a major objective of this study is to measure and analyze the disposable incomes of the urban poor. In addition to data on nominal wages of daily laborer, we therefore need to deflate these wages by an appropriate price index. While one option is simply to use the official CSA food and non-food price indices of each region, these aggregate indices may not reflect the consumption patterns of the poor and do not take into account the urban-rural distinction. We therefore construct a series of poor person’s price indices for urban areas. The method for doing so is quite standard, and such indices have been computed for a number of countries and regions (see, for example, USAID 2009; Sobrado, Demombynes, and Rubiano 2008; and Garner, Johnson, and Kokoski 1996), particularly in more urbanized regions of Latin America (obviously such indices are less relevant for rural food producing households).

To construct such an index for Ethiopia we use the CSA’s Household Income, Consumption and Expenditure Survey (HICES) of 2004/05 (CSA 2007), which has detailed data on household expenditure. We follow a fairly standard practice of defining the poor as the bottom two quintiles of the aggregate expenditure measure.[7] After excluding the non-poor,

[5] de Gobbi (2006) notes that the challenge in the urban areas is not only that the unemployment rate is large but the duration of unemployment is also considerably long. In 2004, about half of unemployed active job seekers could not find job for over 12 months. However, many if not most of these individuals would engage in some form of casual employment. We also note the regional variation in unemployment based on CSA (2011a) data. The largest unemployment rate was registered in Addis Ababa (25 percent) followed by the second biggest city, Dire Dawa (23 percent). The rate in the other relatively large regional states varied between 10–19 percent. There are also big gender differences in unemployment, with female unemployment rates pervasively higher than male unemployment rates.

[6] Of course, measuring rural and urban poverty differentials is very complex in an economy with so much subsistence consumption. Hence it may be that the rural–urban poverty differentials reported by official data are not very precise.

[7] While we might have used the urban poverty line, we note that since urban poverty was just under 40 percent anyway this choice would have been immaterial.

we then compute the expenditure shares for all food and non-food items, and then match these items to those collected in the CSA Consumer Price Survey. Note that since HICES is representative at the rural and urban levels of each region, we compute 22 separate poor person's price indices (PPPIs), or two for each of the 11 regions. Calculating these regionally disaggregated indices is quite important because of significant heterogeneity in consumption patterns across the regions. For example, in the SNNP region *enset* (false banana) is a major staple, but in the rest of the country maize, *teff*, wheat, and some coarse grains are the principles staples (again with variation). Note also that since we are essentially focusing on urban markets (including large rural towns), we only use the urban poor person's price indices.

Given these considerations, the formula for these prices indices (*P*) can be represented by equation (1):

$$P_{r,t} = \sum_{n=1}^{N} s_{n,r} . p_{n,r,t} \qquad (1)$$

Where *r* denotes the region, *t* denotes the month of observation, and *n* denotes the food and non-food items, and $s_{n,r}$ and $p_{n,r,t}$denote the expenditure share of item *n* in region *r* and its market price in month *t*. As a result, we have market level prices indices even though the shares of each item are regional.[8] We also note that these indices are calculated for a food aggregate, a non-food aggregate, and a total CPI. Finally, note that index is set with January 2006 as the base period.

2.3. Hypotheses and econometric tests of the wage–food price relationship

Recall that our second objective was to formally test whether these wages adjust to changing food prices over the short run. We noted that while this hypothesis had been tested in the context of agricultural laborers in Bangladesh and the Philippines, we know of no such extension to other developing countries or to urban areas. In the context of urban Ethiopia we expect relatively little adjustment because of significant slack in labor markets. Urban unemployment hovered at around 20 percent for most of the 2000s, although there is some evidence of a gradual decline as well as a sizeable gender differential in unemployment, with women experiencing higher unemployment than men. Moreover, although higher food prices could stimulate demand for rural labor, it is not obvious that high rural wages would induce urban-to-rural migration, and thereby exert any upward pressure on urban wages.

Are there other mechanisms by which wages might adjust to food prices? Theories of subsistence wages (or efficiency wages) going back to Leibenstein (1957) would suggest that if unskilled informal workers are already being paid a subsistence wage, then their real wages should not fall any further (in other words, nominal wages should adjust to higher food prices). We know of no evidence testing such a hypothesis in Ethiopia, although in some contexts there is observational support for this institution. For example, it may be that one reason why guards and maids are partly paid with food-in-kind is precisely to provide subsistence support and adequate nutrition to function effectively. For casual workers such as daily laborers, however, there are no common norms in this regard, although it is certainly credible that there might exist a real wage floor below which workers would simply be unwilling to work. The existence of such a floor might imply partial wage adjustment to higher food prices.

On the basis of existing theory and the realities of the Ethiopian labor market, our principal hypothesis is that daily laborer wages should exhibit little or no adjustment to higher food prices. To test this hypothesis we use time series econometric techniques appropriate to our

[8] Since Gambella was not included in the HICES we could not produce a PPPI for this region. Hence we just use the regional monthly food and non-food price indices for the 3 markets representing this region.

panel data. The CSA consumer price data constitute a relatively large cross-section (115 markets after dropping four with incomplete data) and a relatively long time series covering 153 months, making it a powerful dataset. However, while there are number of alternative panel regressors available to us, some of these do not perform well with long time series dimensions (such as the increasingly popular dynamic panel GMM methods). Thus we rely on the panel vector error correction model (PVECM). The PVECM can be used to establish if there exists a long term equilibrium relationship between the variables considered and the speed of adjustment towards this relationship in cases of short run disequilibria (such as price shocks). This technique is analogous to the approach adopted by Lasco, Myers, and Bernsten (2008) in a similar context, although Lasco et al. do not have panel data or high frequency data.

To illustrate the model, suppose we want to estimate a vector autoregressive system of equations involving laborers' wages, food, and non-food price indices that we described above. Then the general form of the system of equations is given by:

$$Z_{it} = A_1 Z_{it-1} + \cdots + A_k Z_{it-k} + \mu + \delta t + \xi_{it}, \qquad (2)$$

Where: Z_{it} is a 3 by 1 vector of wages, food, and non-food price index for market i and period t; A_1, ..., A_k are 3 by 3 matrices of unknown variables where k is the lag length; μ is a constant term, which together with the time trend term t is called the deterministic component; ξ_{it} are error terms assumed to be white noise with $\xi_{it} \sim N_p(0, \Sigma_i)$.

After some manipulation equation (2) reduces to the cointegrating relationship:

$$\Delta Z_{it} = \Theta_1 \Delta Z_{it-1} + \Theta_2 \Delta Z_{it-2} + \cdots + \Theta_{k-1} \Delta Z_{it-(k-1)} - \Psi Z_{it-1} + \mu + \delta t + \xi_{it} \qquad (3)$$

where

$$\Theta_{k-1} = -A_k, \ \Theta_{k-1} = -A_k - A_{k-1}, \ \ldots, \ \Theta_1 = -A_k - A_{k-1} - \ldots - A_2,$$

and $\Psi = (I - A_1 - \ldots - A_k)$.

If the variables in Z_{it} are cointegrated, then there exist two 3 by r matrices, α and β, where 3 is the number of variables in Z_{it} and r is the number of cointegrating vectors such that $\Psi = \alpha\beta'$, whereby ΔZ_{it} is stationary and Z_t is non-stationary, but $\beta' Z_t$ is stationary (Johansen 1988, 1991). The cointegrating rank r should be such that $0 < r < 3$. The extreme case in which r=0 implies no cointegration between the variables while if r=3 the variables are cointegrated in levels and there is no need for first differencing of the variables.

Given the non-stationary series, using OLS to estimate (2) will lead to misleading conclusions resulting from two sources. The first is the well documented case of spurious regression in which the variables appear to be related even when they are not, due to their common trend. The second reason is that one of the assumptions of OLS is violated as the error term of the first equation is correlated with the remaining two and vice versa. Given first differences of the variables are stationary and that the variables are related, then the cointegrating equation given by (3) will reveal that relationship. To run this cointegrating relationship we apply the following steps.

First, we apply the Johansen (1988, 1991) method of estimating the cointegrating PVECM given by equation (3). Application of this method proceeds in four steps.[9] The 3 pre-estimation procedures required are determination of the lag length, k, the value of the cointegrating rank, r, and decisions on the deterministic component entering in both the short and long run components of equation (3). Summary results of iterative tests conducted using

[9] This section discusses results of tests conducted on the entire sample. The number of lags and cointegrating vectors and deterministic component selected for the subsamples we use are apparent from the results.

the Fisher/Johansen multivariate panel cointegration tests (due to Maddala and Wu (1999)) are given in Appendix Table B.2. All 11 alternative tests reject the null hypothesis of no cointegration. Results of the panel cointegration test reveal a cointegrating vector of 2 at lag length 1. However, since the model specified with 1 lag and 2 cointegrating vectors performs inferior in terms of LL, AIC, and SIC statistics (results not reported) we selected a model using 1 cointegrating vector. Comparing the performance of the remaining specifications, overall performance, and the significance of coefficients, we selected a model with 3 lags.

One issue worth discussing is the treatment of endogeneity. Hypothetically at least, it is possible that wages could cause food or non-food prices, in addition to or instead of consumer prices causing wages, or that a third factor could simultaneously cause changes in both consumer prices and wages (for example, an expansion in the money supply or a construction boom). Whilst the persistence of unemployment perhaps makes causation from wages to price less likely, the PVECM estimates a full set of equations that allow us to test for reverse causation. As expected, we find very little evidence of significant and substantial reverse causation. As for simultaneous causation, the PVECM partly controls for this influence through several control variables: an autoregressive (AR) terms, time trends, and non-food prices.

3. Results

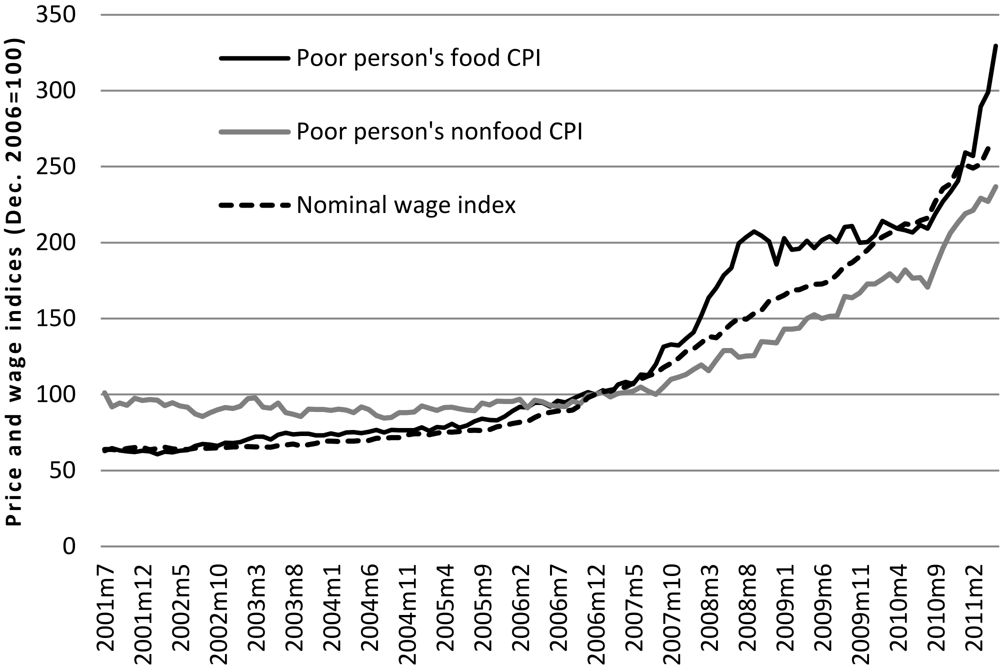
In this section we first describe trends in prices (food and non-food) and wages (real and nominal) for Ethiopia as a whole and for the major regions of the country, before summarizing the results of our econometric tests of short and long run wage–food price relationships.[10]

For our descriptive results the raw market data are averaged across the markets that exist in each of the respective regions to yield regional averages. We also use nationwide nominal and real average wages as a benchmark for relative trends in the five regions while also including the effects of the remaining six regions in a manner that avoids clutter. We also note that although daily wages are measured as a monthly figure in the raw data, we convert the data to daily wages since casual laborers are often contracted on daily terms or piece-meal rates.

We begin with a description of price trends for poor consumers in Ethiopia. Figure 3.1 shows the poor person’s price indices for the food and non-food groups as well as a nominal daily laborer wage index (see Appendix C for a comparison of trends in the poor person’s CPIs to the general CPIs). All three indices are set at 100 for December 2006. All three series trend upwards in a similar fashion, but there are two sharp food price spikes evident in the data, while non-food prices also increased relatively steeply in 2011. The first food price spike began in mid-2007. From that time until mid-2008 food prices essentially doubled, while non-food prices increased by less than half that amount. The second spike was slightly less sharp, with food prices increasing by about 65 percent. We note that these spikes coincide with sharp increases in international prices, although domestic factors (strong economic growth, limited agricultural supply response, and strong growth in money supply) are also thought to be contributing factors.

[10] These five regions together account for 90 percent of the country’s total population and the 11,056 market level monthly observations in these regions constitute 82 percent of the total.

Figure 3.1—Trends in food and non-food nominal prices for the urban poor: 2001–2011



Source: Author's calculations from CSA (2011b) data. See section 2 for methods used.

From Figure 3.1 one can already see that food prices outpaced nominal wage growth in 2007–2008 and 2011. In Figure 3.2 we look at this more closely by deflating nominal wages by the food price index for the urban poor and the total price index for the urban poor.[11] For the ultra-poor, who are likely to spend a very high share of their income on food, it may be that deflating nominal wages by food prices alone is a better indicator of their purchasing power, whereas deflating by the total CPI may be more sensible for somewhat less poor groups.[12]

The distinction is important because when wages are deflated by the total CPI then they show an upward trend over 2001–2011 that is seriously interrupted by the two food price spikes (indeed, at the end of our sample in October 2011 real wages were just 5 percent higher than they were in 2001). However, if one looks at wages deflated only by food prices, then there is no trend, and the shortfalls in disposable income brought about by the two food price hikes are substantial. In 2008 as a whole, for example, food-disposable daily wages were about 15.5 percent lower than they were in 2007, but from a peak in mid-2007 to the trough in September 2008 food-disposable wages fell by around 26 percent. In absolute terms daily wages bottomed out at 8.4 ETB (Ethiopian Birr) per day, or about 0.7 US dollars at the December 2006 exchange rate.[13] When deflated by the total price index for the poor the drop in wages is much smaller in 2008, at about 10 percent.

In 2009 and 2010 food-disposable wages recovered quite strongly and peaked in August of 2010, but from September 2010 to May of 2011 they again fell by around 26 percent.

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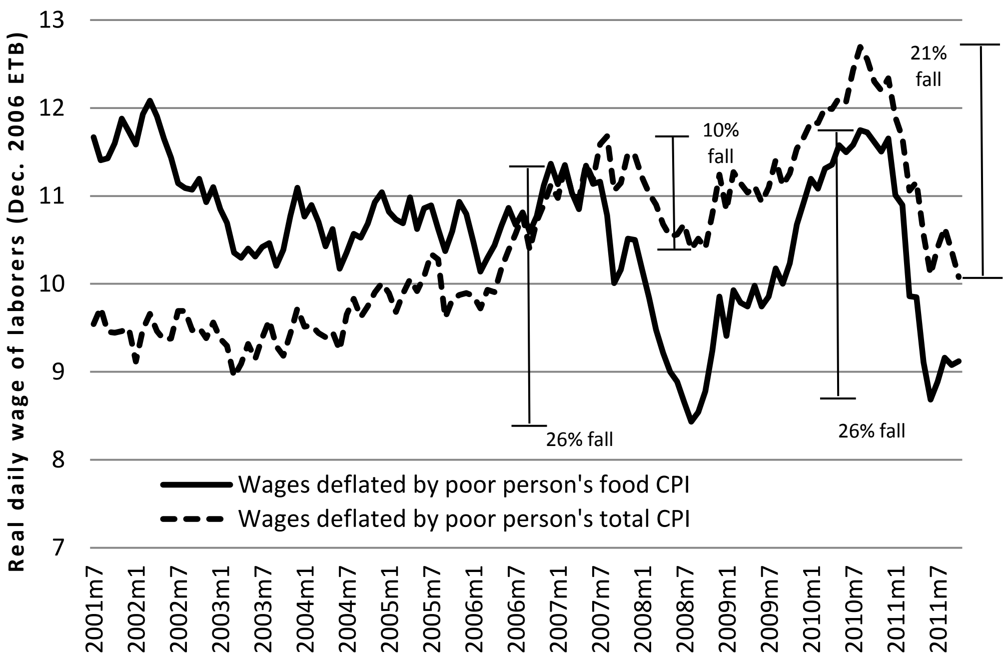
[11] Although our focus here is on daily laborers we note that maid's wages trend very similarly.

[12] Discussion with local experts revealed that many of the urban poor—such as slum dwellers—pay very low rents, suggesting that the vast majority of their income is indeed spent on food. This share would be expected to rise during periods of high real food price changes.

[13] One should not compare this figure of 0.7 US dollars to standard $1.25 per day poverty numbers, since the latters are based on purchasing power parity conversions. Ethiopia's PPP exchange rate is very different from its official exchange rate, with the ratio of the two at about 0.32 in 2005.

Moreover, in 2011 non-food inflation was relatively high (see Figure 3.2), such that the wage series deflated by the total CPI also fell precipitously in 2011, by around 21 percent.

Figure 3.2—Trends in real daily laborer wages deflated by CPIs for the urban poor



Source: Author's calculations from CSA (2011b) data. See section 2 for methods used.

Finally, it is also interesting to observe regional variation in these trends given that we have both region-specific price and wage series. In terms of total population sizes, Oromia, SNNP and Amhara are easily the three biggest regions, while Addis Ababa is easily the largest urban agglomeration. Tigray and Somali region are also sizeable and would have a few million urban inhabitants between them. Tables 3.1 and 3.2 report regionally disaggregated results for wages deflated by the food CPI and the total CPI respectively.

Table 3.1—National and regional trends in daily laborers' wage (2006 ETB), deflated by the poor person's food CPI: 2001–2011

Year	National	Oromia	SNNP	Amhara	Addis	Tigray	Somali
2001	11.7	11.8	9.2	10.0	10.6	14.5	14.2
2002	11.4	11.5	8.9	9.3	10.4	13.9	14.9
2003	10.5	10.4	8.5	8.7	9.4	12.4	14.2
2004	10.7	10.2	9.1	9.3	10.2	12.3	13.5
2005	10.8	10.0	8.9	9.7	11.1	12.7	12.3
2006	10.7	9.8	8.8	10.5	11.3	11.5	11.5
2007	10.9	9.9	8.7	9.6	11.6	12.3	14.2
2008	9.2	7.7	6.8	8.5	10.2	11.4	12.6
2009	10.0	8.5	7.4	9.7	10.8	11.4	14.4
2010	11.5	9.6	9.3	10.4	11.3	12.9	15.4
2011	9.7	8.2	7.6	8.7	9.3	13.0	12.2
Change in wages 2007–2008	-15.5%	-22.4%	-21.8%	-11.5%	-11.8%	-6.8%	-11.2%
Change in wages 2010–2011	-15.8%	-14.2%	-17.4%	-16.5%	-17.4%	0.8%	-20.7%

Source: Author's calculations from CSA (2011b) data. See section 2 for methods used.
Notes: National averages are a weighted average of regional results, with the weights being the number of markets in a region relative to the total number of markets in the country. SNNP = Southern Nations, Nationalities, and Peoples region.

Table 3.2—National and regional trends in daily laborers' wage (2006 ETB), deflated by the poor person's total CPI: 2001–2011

Year	National	Oromia	SNNP	Amhara	Addis	Tigray	Somali
2001	9.5	9.7	7.6	8.6	9.0	12.1	12.9
2002	9.5	9.7	7.3	8.3	8.8	11.9	13.3
2003	9.3	9.5	7.4	8.1	8.6	11.0	13.3
2004	9.7	9.4	8.3	8.6	9.2	10.7	13.0
2005	9.9	9.4	8.5	9.1	10.3	11.5	12.0
2006	10.4	9.7	8.9	10.1	10.7	11.3	11.7
2007	11.3	10.5	9.2	10.0	12.3	13.5	15.3
2008	10.8	9.4	8.3	9.9	11.9	13.6	15.1
2009	11.2	9.8	8.6	10.8	12.1	13.4	16.0
2010	12.2	10.6	10.0	10.9	11.7	14.6	17.3
2011	10.9	9.9	9.1	9.5	10.0	14.7	15.9
Change in wages 2007–2008	-4.9%	-11.0%	-9.8%	-1.5%	-3.4%	0.9%	-1.4%
Change in wages 2010–2011	-10.4%	-7.3%	-8.5%	-13.0%	-15.0%	0.3%	-8.3%

Source: Author's calculations from CSA (2011b) data. See section 2 for methods used.
Notes: National averages are a weighted average of regional results, with the weights being the number of markets in a region relative to the total number of markets in the country. SNNP = Southern Nations, Nationalities, and Peoples region.

In Table 3.1 what is most striking is that the two most populous regions in the country saw the largest food-disposable income declines in 2008 (22.4 percent in Oromia and 21.8 percent in SNNP, while the Amhara, Addis, and Somali regions saw smaller declines (11–12 percent) and Tigray smaller again (6.8 percent). However, in the 2011 food price spike there was not much regional variation in food-disposable income, except in Tigray in which there was essentially no change. This suggests that Tigray's labor market is not well integrated with the rest of the country, and that local economic forces in that region are driving up wages there.[14]

In terms of the wage series deflated by the total CPI (Table 3.2), we see a similar pattern of results, but also that the 2008 crisis was not as severe as the 2011 crisis. In 2008, real wages declined by 10 percent in the two largest regions (Oromia and SSNP), but most other regions saw only modest declines in real wages. In 2010–2011, however, all regions except Tigray experienced real wages declines of 7 percent or more, with Addis Ababa and Amhara seeing 15 percent and 13 percent real wages declines, respectively.

We now turn to formally testing whether daily laborer wages respond to price changes over the short run. From the trends observed in the previous section it is already clear that wages certainly did not fully respond to the sharp food price spikes of 2008 and 2011, but we may still observe some adjustment. Moreover, the PVECM allows us to distinguish between long run adjustments represented by cointegrating equations, and short run adjustments represented by the speed at which short run price-wage differences dissipate. For welfare purposes, we are of course much more interested in the issue of short run adjustment, but in the interests of full reporting we report the long run cointegrating relationship in equation (4):

$$Wages = -2.95 + 1.24{*}Food\ CPI - 0.10{*}\ Non\text{-}food\ CPI - 0.0001{*}\ t + e_{it} \quad (4)$$

We note that only the long run coefficient on the food CPI is significant at conventional levels (at the 1 percent level). Hence, in the long run wages only adjust to food prices. Moreover, the 95 percent confidence interval for the long run wage–food price elasticity is between 1.12 and 1.36, implying that the elasticity is significantly different larger than unity. In terms of robustness tests we derived cointegrating relationships for each region, but found no substantial differences for any of the major regions. For example, the long run wage–food price elasticities for Oromia (0.97), SNNP (1.21), Amhara (1.11), and Addis Ababa (0.90) are all significant at the 1 percent level and not radically different from each other or from the elasticity for the entire country (1.24). We also estimated these coefficients for different town and city sizes, in which we found wage–food price elasticities were somewhat smaller in larger cities of more than 30,000 people (1.12) than in smaller towns of less than 30,000 people (1.27). In all equations the elasticity with respect to non-food prices was not significantly different from zero.

Bearing in mind Keynes' famous quip that in the long run we are all dead, we should perhaps be less interested in the cointegrating relationships discussed above, and more concerned with short run adjustment coefficients. In Table 3.3 we report short run PVECM results for the full sample, followed by results for sub-samples of larger cities, smaller rural towns, and the three largest regions plus the largest city, Addis Ababa. The pertinent coefficients are those on the lagged changes in the food price index (FPI) of the urban poor. In general the first lag of the FPI is always significant with the expected negative sign, while the second lag is also often significant. However, the coefficients are very small (-0.039 to -0.062), implying that a short run shock to food prices only leads to a very marginal change in wages. There is little variation across samples, although in SNNP only the third lag of the FPI is significant (and then only marginally so at the 10 percent level) while the FPI coefficients are slightly higher for Addis Ababa. Interestingly, there is no short run wage adjustment to non-food price shocks in any of the samples.

[14] While we should not rule out some amount of measurement error (only 8 markets are surveyed in Tigray, which amounts to about 21 observations in total), anecdotal evidence also suggests heightened economic activity in Tigray. This is based on personal communication with colleagues currently working in Tigray.

Table 3.3—Short run adjustment coefficients of panel vector error correction (PVEC), July 2001–October 2011

Regression No.	1	2	3	4	5	6	7
Sample	Full	Cities>20K	Towns>20K	SNNP	Addis	Amhara	Oromia
Δ Waget-1	-0.356***	-0.354***	-0.355***	-0.333***	-0.285***	-0.337***	-0.387***
	(0.009)	(0.014)	(0.011)	(0.017)	(0.029)	(0.022)	(0.019)
Δ Waget-2	-0.147***	-0.152***	-0.143***	-0.096***	-0.133***	-0.151***	-0.139***
	(0.009)	(0.015)	(0.012)	(0.018)	(0.029)	(0.022)	(0.02)
Δ Waget-3	-0.081***	-0.069***	-0.085***	-0.068***	-0.043	-0.099***	-0.044**
	(0.008)	(0.014)	(0.011)	(0.016)	(0.027)	(0.021)	(0.019)
Δ FPIt-1	-0.039***	-0.038**	-0.041***	-0.057**	0.028	-0.062**	-0.038*
	(0.010)	(0.016)	(0.014)	(0.025)	(0.038)	(0.024)	(0.022)
Δ FPIt-2	-0.028**	-0.012	-0.037**	-0.067**	0.034	-0.045*	-0.013
	(0.011)	(0.017)	(0.015)	(0.027)	(0.04)	(0.025)	(0.024)
Δ FPIt-3	0.014	0.019	0.01	-0.037	0.018	-0.001	0.035
	(0.01)	(0.015)	(0.013)	(0.024)	(0.037)	(0.023)	(0.022)
Δ NFPIt-1	-0.004	0.006	-0.013	0.011	-0.007	-0.004	-0.003
	(0.007)	(0.009)	(0.01)	(0.016)	(0.015)	(0.02)	(0.017)
Δ NFPIt-2	0.007	0.002	0.011	0.029	0.003	-0.008	0.022
	(0.008)	(0.01)	(0.011)	(0.018)	(0.016)	(0.022)	(0.019)
Δ NFPIt-3	0.002	0.000	0.003	0.009	0.007	-0.003	-0.005
	(0.007)	(0.009)	(0.01)	(0.016)	(0.015)	(0.02)	(0.017)
Constant	0.02***	0.02***	0.02***	0.021***	0.017***	0.023***	0.018***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)	(0.002)
F/Chi-squared statistic[a]	281	155	137	65	18	38	56
Number of observations	13,571	5,343	8,228	3549	1428	2,240	2,839

Source: Analysis using CSA (2011b) data.
Notes: The dependent variable if first difference log of wage of laborers. Coefficients with superscripts ***, **, and * are significant at 1, 5, and 10 percent levels, respectively. Standard errors are in parentheses. FPI and NFPI stand for food price index and non-food price index, respectively. [a] While the F-statistics are associated with vector Error correction and fixed effects models the chi-squared statistics are associated with the panel data instrumental variables models. The coefficients are jointly significant at 1 percent in all models. SNNP = Southern Nations, Nationalities, and Peoples region.

In terms of robustness checks, we also ran fixed effects models in first differences and GMM regressions, but these also displayed very similar results: the same patterns of significance and insignificance, and very similar point estimates on the coefficients of relevance. Of course, these results are not very surprising given the descriptive data in Figures 3.1 and 3.2, but they at least formally confirm the weak response of wages to food price innovations.

4. Conclusions

This research posed two objectives. First, in light of its exceptionally rapid food inflation, we sought to identify trends in the purchasing power of casual wages in the cities and rural towns of Ethiopia. And second, in light of a very sparse literature on wages and food prices, we aimed to formally test whether casual wages in these predominantly urban areas adjusted to higher food prices, and if so, to what degree.

On the first of these objectives we found a sharp deterioration in the food purchasing power of wages from mid-2007 to mid-2008, when food prices first spiked, and again in mid-2011. In the 2007–2008 spike, the food purchasing power of these wages declined by around 20 percent. The overall purchasing power (that is, factoring in trends in non-food prices) declined by around 10 percent. Admittedly, the period of significant decline in purchasing power lasted less than a year (around 4–5 months in 2008), but the rapid deterioration in urban welfare was significant, is corroborated by other survey evidence (Alem and Söderbom 2012), and consistent with simulation evidence (Dessus, Herrera, and de Hoyos 2008). Our data also suggest that the 2010–2011 food crisis had larger welfare impacts than the 2008 crisis because of more rapid non-food inflation. On the second objective, our econometric results were consistent with our descriptive results: we observe a sizeable long run adjustment of wages to food prices, but very little short run adjustment.

Although our results are supported by some existing evidence, they arguably give a different message to the most recent official poverty results for Ethiopia, which are derived from the CSA's 2004/05 and 2010/11 HICE surveys. Those results conclude that urban total poverty fell from 35.1 percent in 2004/05 to 25.7 percent in 2010/11, while urban food poverty fell from 35.3 percent to 27.9 percent. In contrast, we found that urban wages in mid-2011 were only fractionally higher than they were in 2005. One obvious explanation for the apparent contradiction may simply be related to timing issues. Somewhat unusually, the 2010/11 HICE survey took place over a 12 month period (July 2010 to July 2011). At the start of that period real urban wages were about 9 percent higher than they were in 2005, but by July of 2011 real urban wages were 16 percent lower than they were in 2005. Why? Because in the 12 month period in which the 2010/11 HICES was conducted the poor person's food price index rose by 60 percent and the non-food price index rose by 40 percent. This suggests that the HICES results could be very sensitive to the timing of the survey and the accurate matching of household expenditure responses to appropriately timed food and non-food price observations. That said, there could obviously be other legitimate explanations of some discrepancy between the two results, such as the surprisingly large decline in urban inequality observed in the HICES data. We also note that the most recent Demographic Health Survey for Ethiopia (2010/11) shows substantial progress on various non-income indicators of health, education, and nutrition in both rural and urban areas. So, secular welfare trends in Ethiopia are by no means unfavorable from a broader point of view.

What are the research and policy implications of these findings? Following Deaton and Dreze (2002), albeit in a more urban setting, we argue that this kind of casual wage data constitutes a very useful high frequency welfare indicator for the urban poor, especially in periods of volatile prices. Currently, however, very few developing countries collect and report this kind of data. The Ethiopian CSA's approach of collecting casual wage data through its consumer price survey seems a cost-effective means of doing so, although further validation of the data would indeed be ideal.

On the issue of wage–food price adjustments, our formal tests indicate a very weak short run relationship. Future research could test this in other settings. For example, while Ethiopia appears to be a surplus labor economy, some of the fast growing economies of Asia appear to have already passed the Lewis turning point (Zhang, Yang, and Wang 2010), suggesting that food price inflation there may lead to greater wage adjustments. Given the high degree of food price volatility witnessed around the world in the past decade—and the likely prospect of ongoing volatility in years to come (Headey, Fan, and Malaiyandi 2010)—understanding wage behavior in this regard constitutes an important research agenda.

In terms of policy implications, it is difficult to draw concrete prescriptions on this front. One obvious question that arises from our findings is whether more interventions are needed to protect the urban poor in Ethiopia, particularly from food price volatility. To date, most of Ethiopia's food security interventions have been directed towards rural areas, such as the Productive Safety Nets Program (PSNP). For the most part this heavy rural focus is quite justifiable. According to our estimates from the most recent (2010/11) poverty report for Ethiopia (CSA 2012), there are around 20.7 million $1.25/day poor in rural areas and just 3.8 million in urban areas. Hence around 80 percent of Ethiopia's $1.25/day poor reside in rural areas. Similar ratios exist for nutrition indicators.[15] That said it is theoretically probable that the urban poor are more vulnerable to food price volatility than the rural poor. Given the country's exceptionally rapid food inflation in recent years, a much stronger rationale for food security interventions in urban areas has certainly emerged.

In the wake of the 2008 crisis the Ethiopian government's strategy on this front has primarily consisted of directly attempting to reduce food price volatility through price controls and the stocking and destocking of strategic grain reserves. However, given that food prices again rose very sharply in 2011 it appears that attempts to prevent food inflation have not been sufficiently effective. Further research into the drivers of price inflation in Ethiopia could shed light on how inflation might be curbed in the future,[16] but given that Ethiopia is a large importer of food, some amount of internationally induced inflation may be more or less inevitable. If that is indeed the case then this might justify a need for some type of urban social safety net. Among other considerations,[17] such a program would need to carefully appraise how best to effectively protect the urban poor from price volatility. In the 2008 crisis, for example, the rural PSNP did not fully index its cash payment components to rapid food inflation (Sabates-Wheeler and Devereux 2010). Indexing cash payments to a price index—such as the poor person's price index developed in this paper—would seem an effective means for preventing that kind of recurrence.

[15] It should be noted that it is often difficult to precisely measure rural–urban poverty differentials very precisely since it requires a proper accounting of income or expenditure and of rural–urban price differences. In that regard non-monetary indicators may be better, such as rural and urban malnutrition comparisons. On that front the 2005 Demographic Health Survey suggests that around 18.1 percent of urban women had low body mass in 2005, while 24.5 percent was the corresponding rate for rural Ethiopia. However, for children the difference was even larger: 31.7 percent were estimated to be stunted in urban areas, but 47.6 percent were stunted in rural areas.

[16] While there is clearly a close correlation between international food prices and Ethiopia's domestic food prices, some analysts have suggested that expansionary macroeconomic policies have also contributed to the inflation. The government has also cited inadequate competition among traders and importers. The government also placed high priority on agricultural production, but even if effective it would take many years to achieve anything close to self-sufficiency in food.

[17] There are, of course, many factors that would need to be considered in assessing the need for an urban social safety net, such as whether the urban poor are really as food insecure as rural populations, or whether they are in fact more vulnerable to other kinds of shocks, such as health shocks.

Appendix

Appendix A. Additional details of the CSA consumer price survey locations

Table A.1—Selected market places from the 11 regional states

Region	Market name	Location classification	Total population
Tigray	Endaselassie	Rural	7981
Tigray	Endagobana	Rural	10107
Tigray	Adwa	Urban	40502
Tigray	Axum	Urban	44629
Tigray	Adigrat	Urban	57572
Tigray	Wukro	Urban	30208
Tigray	Maichwe	Rural	23484
Tigray	Mekelle	Urban	122850
Afar	Aysaita	Rural	16048
Afar	Dubti	Rural	15317
Afar	Melka werer	Rural	7813
Afar	Awash 7 Kilo	Rural	14875
Amhara	Chuahit	Rural	6814
Amhara	Gondar	Urban	206987
Amhara	Este/Mekane Yesus	Rural	13902
Amhara	Debre Tabor	Urban	55157
Amhara	Kobo	Rural	24861
Amhara	Woldia	Urban	46126
Amhara	Kombolcha	Rural	N.A.
Amhara	Dessie	Urban	120029
Amhara	Shewa Robit	Rural	17573
Amhara	Debre Birhan	Urban	65214
Amhara	Mota	Rural	26173
Amhara	Debre Markos	Urban	62469
Amhara	Bahir Dar	Urban	155355
Amhara	Sekota	Rural	22342
Amhara	Made Work	Rural	4205
Amhara	Dangla	Rural	24564
Amhara	Chagni	Rural	23225
Amhara	Kebese	Rural	36116
Oromia	Gimbi	Rural	8492
Oromia	Dembi Dolo	Rural	29249
Oromia	Shambu	Rural	15798
Oromia	Nekemt	Urban	76817
Oromia	Bedele	Rural	19504
Oromia	Metu	Rural	29627
Oromia	Jimma	Urban	120600
Oromia	Agaro	Rural	25719
Oromia	Ambo	Urban	50267

Region	Market name	Location classification	Total population
Oromia	Woliso	Urban	37867
Oromia	Ejire	Rural	8462
Oromia	Fiche	Rural	27487
Oromia	Nazareth	Urban	222035
Oromia	Shashemene	Urban	102062
Oromia	Dixis	Rural	6979
Oromia	Assela	Urban	67250
Oromia	Assebe Teferi	Rural	11642
Oromia	Bedessa	Rural	18183
Oromia	Alemaya	Urban	31686
Oromia	Boroda	Rural	2630
Oromia	Adaba	Rural	12090
Oromia	Robe	Urban	62460
Oromia	hagere Mariam	Rural	26600
Oromia	Negele	Rural	N.A.
Somali	Shinille	Rural	7206
Somali	Erer	Rural	5612
Somali	Jigjiga	Urban	125584
Somali	Hartishek	Rural	1858
Somali	Dollo	Rural	2745
Somali	Moyalle	Rural	1129
Ben-Gumuz	Mambuk	Rural	7025
Ben-Gumuz	Mender 7	Rural	N.A.
Ben-Gumuz	Assosa	Rural	22725
Ben-Gumuz	N.A.	Rural	1189
Ben-Gumuz	kemashi	Rural	796
Ben-Gumuz	N.A.	Urban	69957
SNNP	Wolkite	Rural	28856
SNNP	Butajira	Urban	33393
SNNP	Hosaena	Urban	69957
SNNP	Shone	Rural	15611
SNNP	Doyogena	Rural	6718
SNNP	Alaba	Rural	8111
SNNP	Awassa	Urban	158273
SNNP	Hagere selam	Rural	24454
SNNP	Dilla	Urban	81644
SNNP	Yirga chefe	Rural	15919
SNNP	Wolayita Sodo	Urban	76780
SNNP	Bodity	Rural	27684
SNNP	Jinka	Rural	20522
SNNP	Dimeka	Rural	N.A.
SNNP	Masha	Rural	4159
SNNP	Teppi	Rural	24489
SNNP	Bonga	Rural	20855

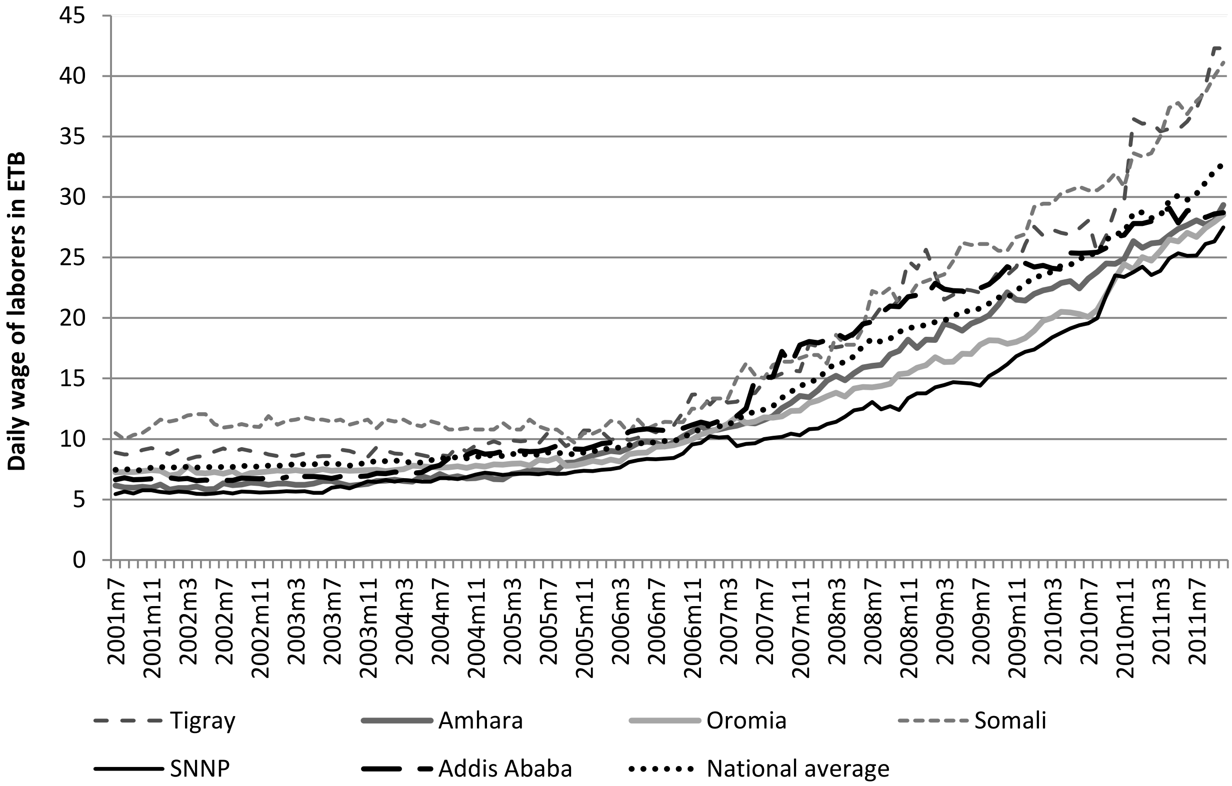
Region	Market name	Location classification	Total population
SNNP	Chana	Rural	8063
SNNP	Arba Minch	Urban	74843
SNNP	Sawla	Rural	23370
SNNP	Shewa Benchi	Rural	3374
SNNP	Mizan Teferi	Rural	4311
SNNP	Kele	Rural	12850
SNNP	Soyama	Rural	6268
SNNP	karat	Rural	5784
SNNP	Gidole	Rural	13176
SNNP	N.A.	Rural	N.A.
SNNP	Bestechire	Rural	15850
SNNP	Lasoka	Rural	2985
SNNP	Amaya	Rural	4824
Gambella	Gambella	Urban	38994
Gambella	Shebo Kire	Rural	N.A.
Gambella	N.A.	Rural	N.A.
Harar	Harar - Arategna	Urban	183344
Addis Ababa	AA - Merkato	Urban	2738248
Addis Ababa	AA - Kera	Urban	2738248
Addis Ababa	AA - Zenebe Work	Urban	2738248
Addis Ababa	AA - Gerji	Urban	2738248
Addis Ababa	AA - Saris	Urban	2738248
Addis Ababa	AA - Kotebe	Urban	2738248
Addis Ababa	AA - Ferensay Legasion	Urban	2738248
Addis Ababa	AA - Sholla	Urban	2738248
Addis Ababa	AA - Asko	Urban	2738248
Addis Ababa	AA - Adissu Gebeya	Urban	2738248
Addis Ababa	AA - Efoyta Gebeya	Urban	2738248
Addis Ababa	AA - Akaki	Urban	2738248
Dire Dawa	DD - Sabian	Urban	342827
Dire Dawa	Melka Jebdu	Urban	342827

Source: CSA (2011b), with population estimates provided by the authors from the 2007 CSA Census.
Notes: N.A. means not available. In some cases the markets and/or their population sizes could not be identified. In such cases we classified these markets as rural. SNNP = Southern Nations, Nationalities, and Peoples region.

Appendix B. Econometric issues

The first step in selection of models to apply on time series data involves checking if the data are stationary and determination of the order if non-stationarity is detected. Together, Figures 1.1 and 3.1 indicate that the wage and food and non-food price indices are clearly non-stationary. In this section we first provide formal tests on the wage and price indices series used in the following subsection. Having ascertained the non-stationarity of the series we then describe the vector error correction model (VECM) and the panel data fixed effects and instrumental variables models used in the analysis and finally results of tests conducted to use the VECM.

Figure B.1—Trends in average daily wages of laborers, July 2001–October 2011



Source: CSA (2011b) data.
Note: SNNP = Southern Nations, Nationalities, and Peoples region.

Before conducting the panel unit-root tests we first checked stationarity for the wage, food, and non-food price index series for all 115 markets. Summary results of these panel unit-root tests are presented in Table B.1. The methods used to test the null hypothesis that the series are unit-root cannot be rejected at any level while the method due to Hardi, which pertains to a null-hypothesis that all the series are stationary, is rejected at all acceptable levels. By contrast the null-hypothesis that first difference of the series have unit-roots is rejected at all acceptable levels in the four methods used. The Hardi method that hypothesizes first differences of all series are stationary is also rejected, contradicting the results implied by other tests. Given that the three series tested are stationary when each market is considered separately we proceed assuming that the series are unit-root processes in levels and stationary in first-differences. Note that we also ran individual unit-root tests for each market. At a 10 percent level of significance no wage series resulted in a rejection of the null hypothesis of a unit-root process, while only one market resulted in a rejection for the food price index and the non-food price index. Yet as expected, the null hypothesis of unit-root of first differences of the three series was rejected in all markets at all significance levels, with a p-value of 0.00. Hence it appears that the panel as a whole is characterized by unit-root processes and is integrated of order 1.

Table B.1—Summary statistics of panel unit-root (UR) tests

Series		Variable	Methods					
			Levin, Lin & Chu[a]	Breitung[b]	Im, Pesaran and Shin[b]	Fisher, ADF[b]	Fisher, PP[b]	Hardi
Levels	Wages	Statistic	11.7	2	19	25	39	46
		P-value	1.00	0.98	1.00	1.00	1.00	0.00
	Food CPI	Statistic	21	15	28	12	20	42
		P-value	1.00	1.00	1.00	1.00	1.00	0.00
	Non-food CPI	Statistic	14	6	19	38	93	53
		P-value	1.0	1.0	1.0	1.0	1.0	0
First differences	Wages	Statistic	-48	-32	-77	4973	8160	4
		P-value	0.00	0.00	0.00	0.00	0.00	0.00
	Food CPI	Statistic	-31	-10	-70	4422	8835	2
		P-value	0.00	0.00	0.00	0.00	0.00	0.01
	Non-food CPI	Statistic	-49	-31	-80	5234	8857	5
		P-value	0.00	0.00	0.00	0.00	0.00	0.00

Source: Analysis using CSA (2011b) data.
Notes: Methods with superscripts a or b have the null-hypothesis that the series are unit-root with common and individual unit-root processes, respectively. The null hypothesis of Hardi's test is that all the series are stationary. Tests are conducted on natural log of wage and price index series.

Given that the wage and price index series are non-stationary application of OLS on these data will lead to erroneous estimates. Hence we use the panel data vector error correction model (PVECM) since it has the attractive feature of separating the short and long run elasticities, and also considers the variables as an endogenous system. In addition we also use the standard fixed effects panel data model specified to account for short and long run effects as well as the panel data instrumentals methods, which performs better than dynamic panel data models (i.e. dynamic panel GMM) in long time series data. We complement the PVECM with the latter two as the study is interested primarily in the short run effects of food price inflation on wages.[18]

Suppose we want to estimate a vector autoregressive system of equations involving laborers' wages, food, and non-food price indices that we described above. Then the general form of the system of equations is given by:[19]

$$Z_{it} = A_1 Z_{it-1} + \cdots + A_k Z_{it-k} + \mu + \delta t + \xi_{it}, \qquad (2)$$

Where: Z_{it} is a 3 by 1 vector of wages, food, and non-food price index for market I ($i \in [1, 115]$) and period t, ($t \in [1, 119]$); A_1, ..., A_k are 3 by 3 matrices of unknown variables where k is the lag length; μ is a constant term, which together with the time trend term t is called the deterministic component; ξ_{it} are error terms assumed to be white noise with $\xi_{it} \sim N_p(0, \Sigma_i)$.

[18] Time series vector error correction models are standard in this setting and there are existing applications to time series wage–price data. Previous research include includes Ravallion (1990), Rashid (2002), and Lasco, Myers, and Bernsten (2008). This study uses the panel data version of this model. However, the tests used are largely the same as on the simple time series models and we present results of these tests without going through the details. Please refer Baltagi (2005) for additional reference.
[19] A more general form may include a vector of exogenous variables assumed to affect the three series. Since we do not have market level data other than prices we do not pursue this specification.

After some manipulation equation (2) reduces to the cointegrating relationship:

$$\Delta Z_{it} = \Theta_1 \Delta Z_{it-1} + \Theta_2 \Delta Z_{it-2} + \cdots + \Theta_{k-1} \Delta Z_{it-(k-1)} - \Psi Z_{it-1} + \mu + \delta t + \xi_{it} \tag{3}$$

where $\Theta_{k-1} = -A_k$, $\Theta_{k-1} = -A_k - A_{k-1}$, …, $\Theta_1 = -A_k - A_{k-1} - ... - A_2$,

and $\Psi = (I - A_1 - ... - A_k)$.

If the variables in Z_{it} have a long term equilibrium, in which case we claim that they are cointegrated, then there exist two 3 by r matrices, α and β , where 3 is the number of variables in Z_{it} and r is the number of cointegrating vectors such that $\Psi = \alpha\beta'$, whereby ΔZ_{it} is stationary and Z_t is non-stationary, but $\beta' Z_t$ is stationary (Johansen 1988, 1991). The cointegrating rank r should be such that $0 < r < 3$. The extreme cases in which r=0 implies no cointegration between the variables while if r=3 the variables are cointegrated in levels and there is no need for first differencing of the variables.

Given the non-stationary series, using OLS to estimate (2) will lead to misleading conclusions resulting from two sources. The first is the well documented case of spurious regression in which the variables appear to be related even when they are not, due to their common trend. The second reason is that one of the assumptions of OLS is violated as the error term of the first equation is correlated with the remaining 2 and vice versa. Given first differences of the variables are stationary if indeed the variables are related then the cointegrating equation given by (3) will reveal that relationship. To run this cointegrating relationship we apply the following steps.

First, we apply the Johansen (1988, 1991) method of estimating the cointegrating PVECM given by equation (3). Application of this method proceeds in four steps.[20] The 3 pre-estimation procedures required are determination of the lag length, k, the value of the cointegrating rank, r, and decisions on the deterministic component entering in both the short and long run components of equation (3). Summary results of iterative tests conducted using the Fisher/Johansen multivariate panel cointegration tests (due to Maddala and Wu (1999)) are given in Table B.2. We also conducted the Pedroni and Kao Engle-Granger two-step residual based tests. These tests first apply OLS on the original system and test for stationarity of the residuals obtained in the first step by running a second step regression. The two differ in their specification of the first step regression. All 11 alternatives available in the Pedroni method reject the null hypothesis of no cointegration under each of the three deterministic options of trend and intercept as does the Kao panel cointegration test.

[20] This section discusses results of tests conducted on the entire sample. Number of lags and cointegrating vectors and deterministic component selected for the subsamples we use are apparent from the results.

Table B.2—Results of the Johansen/Fisher panel cointegration tests

Number of lags (k)	Null hypothesis on cointegrating rank, r	Fisher test statistics and P-values				LL, AIC, and SIC of model with r=1*
		Trace	P-value	Max. eigen value	P-value	
	r = 0	1035	0.00	873	0.00	31444
1	r ≤ 1	385	0.00	331	0.00	-4.55
	r ≤ 2	217	0.72	217	0.72	-4.54
	r = 0	607	0.00	514	0.00	31980
2	r ≤ 1	264	0.06	212	0.80	-4.67
	r ≤ 2	196	0.95	196	0.95	-4.65
	r = 0	533	0.00	496	0.00	32038
3	r ≤ 1	210	0.83	163	1.00	-4.72
	r ≤ 2	180	0.99	180	0.99	-4.70
	r = 0	508	0.00	470	0.00	31988
4	r ≤ 1	194	0.96	151	1.00	-4.75
	r ≤ 2	172	1.00	172	1.00	-4.72
	r = 0	459	0.00	417	0.00	32150
5	r ≤ 1	196	0.95	152	1.00	-4.81
	r ≤ 2	174	1.00	174	1.00	-4.78
	r = 0	529	0.00	457	0.00	32027
6	r ≤ 1	201	0.92	164	1.00	-4.83
	r ≤ 2	167	1.00	167	1.00	-4.80

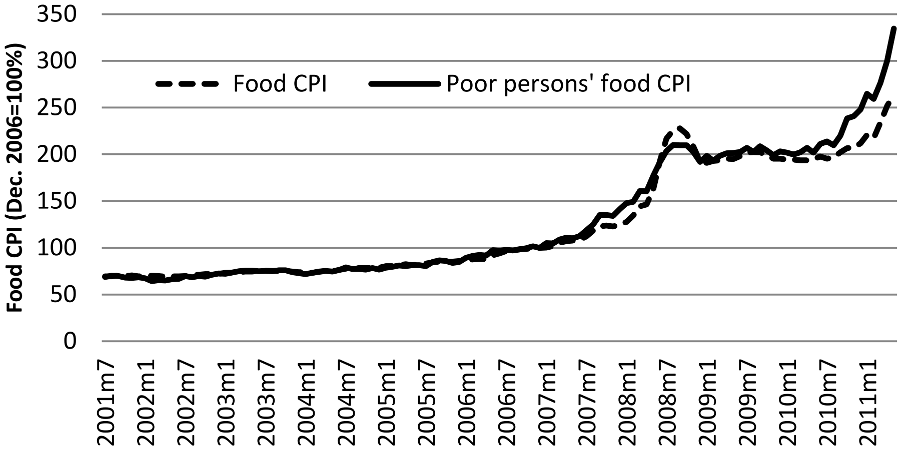
Source: Analysis using CSA (2011b) data.
Notes: * LL, AIC, and SIC stand for log likelihood, Akaike, and Schwarz information criterion, respectively, and the numbers in the column are put in that order. The PVECM is specified to include an intercept and linear trend in the cointegrating equation and an intercept in the vector autoregressive component.

Consistent with the two residual-based tests, the Johansen-Fisher tests rejected the null hypothesis of no cointegration in all deterministic component specifications. Among the five alternative deterministic component specifications we selected the one using an intercept and time trend in the long term cointegrating equation and an intercept in the short run component. Those using a constant and trend in both components have similar implications.

Results of the panel cointegration test using this specification reject the null hypothesis of no cointegration at all lag lengths. However, the test reveals a cointegrating vector of 2 at lag length 1. However, since the model specified with 1 lag and 2 cointegrating vectors performs inferior in terms of LL, AIC and SIC (not shown in the table) we selected a model using 1 cointegrating vector. Moreover, given that we use monthly data a specification of more lags was found to be appropriate. Comparing the performance of the remaining specifications, overall performance, and the significance of coefficients, we therefore selected a model with 3 lags.

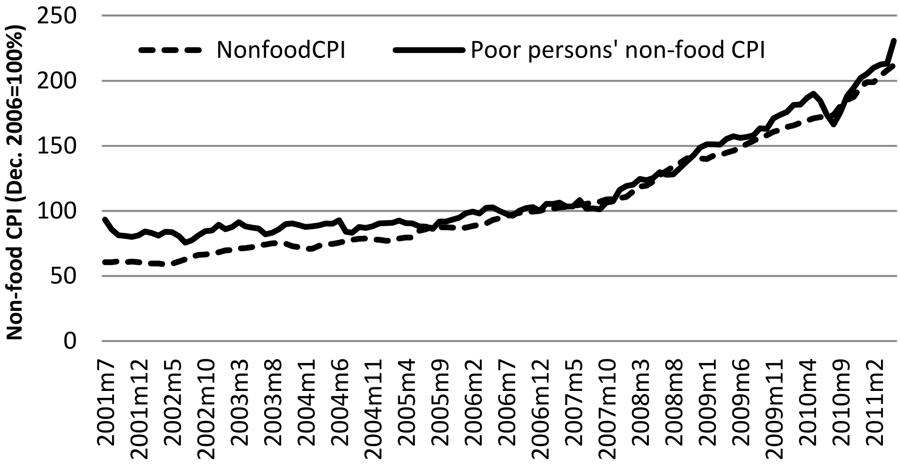
Appendix C. Comparisons of poor person's price indices to aggregate price indices

Figure C.1—Comparing food indices



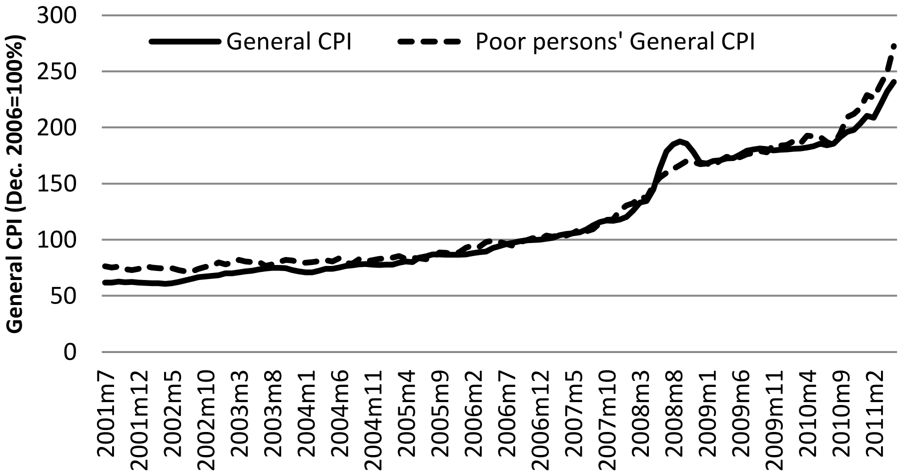
Source: Author's calculations from CSA (2011b) data

Figure C.2—Comparing non-food indices



Source: Author's calculations from CSA (2011b) data

Figure C.3—Comparing total price indices



Source: Author's calculations from CSA (2011b) data

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