ETHIOPIA

IFPRI

የኢትዮጵያ ፌዴራላዊ ዲሞክራሲያዊ ሪፐብሊክ
ፖሊሲ ጥናት ኢንስቲትዩት
THE FEDERAL DEMOCRATIC REPUBLIC OF ETHIOPIA
POLICY STUDIES INSTITUTE

STRATEGY SUPPORT PROGRAM | WORKING PAPER 134 AUGUST 2019

The rising costs of nutritious foods: The case of Ethiopia

Fantu Nisrane Bachewe and Bart Minten

CONTENTS

TABLES

FIGURES

ABSTRACT

Costs of healthy diets are worryingly rising in a number of developed and emerging economies. However, less is known on these costs for developing countries. Using price data from a large number of markets in Ethiopia, we find that real prices of all nutritionally-rich food groups increased significantly (between 19 and 62 percent) over the period 2007 to 2016. This contrasts with (1) staple crops (grains, roots, and tubers), which did not show any price increase, and (2) oils, fats, and sugar, the prices of which decreased substantially. Using detailed nationwide datasets and relying on time series methods, we link these price increases to changes in local markets, demand and supply factors, transaction costs, and international trade. We find that prices of nutritionally-rich food groups – compared to cereals – are relatively less affected by international trade and exchange rate changes but more so by rapidly increasing local and city demand. This rising demand is likely due to recent income growth and rapid urbanization and the high-income elasticities for nutritious foods in Ethiopia. Moreover, we find that local production changes affected prices of nutritious items little, but national price rises were found to have been significantly linked with food price rises in commercial clusters in the country. Changes in transaction costs – fuel and transport costs – explained relatively little of the observed food price changes.

1. INTRODUCTION

It was estimated in 2018 that globally 22, 7, and 6 percent of children were stunted, wasted, or overweight, respectively (Development Initiatives 2018). Food consumption patterns are seen as a crucial cause for this dire situation, so providing improved access to affordable healthy food is receiving increasing attention. To inform appropriate food price policies, understanding access to healthy foods and the determinants of their prices is important. Most studies in this area have focused on developed countries and on the link, in particular, between obesity and the lack of access (food deserts) and consequent high prices of healthy foods (e.g., Aggarwal et al. 2012; Han and Powell 2011; Xu et al. 2014; Powell et al. 2013). In emerging economies, Wiggins et al. (2015) have documented rapid increases in the cost of healthy diets.

However, limited research has been done on the evolution of the prices of healthy foods and on factors associated with these price changes in poorer countries.[1] Given the high prevalence of undernutrition among children in low income countries and the associated high human and economic costs (Hoddinott et al. 2013), improving nutritional outcomes is an urgent priority for these countries. Lack of access to diverse diets has been shown to be one of the major underlying factors contributing to chronic undernutrition (Arimond and Ruel 2004; UNICEF 1998). Recent research shows that prices of nutritious foods in developing countries are relatively high (Headey et al. 2018) or access is limited (Headey et al. 2019). Increasing efforts are needed to stimulate greater local access to nutritious foods in such countries.[2]

In this paper, we explore the evidence on and investigate the determinants of rising prices of nutritious foods in Ethiopia, the second most populous country in Africa, over the period 2007 to 2016. Improving nutrition is high on the policy agenda of the government of Ethiopia, as stated in the Growth and Transformation Plan II, which aims to reduce young child stunting levels from 40 percent in 2014/15 to 26 percent in 2019/2020. Despite recent improvements, child stunting in

[1] For exceptions, see Brinkman et al. (2011) and Iannotti et al. (2012).

[2] Yet, even with sufficient access to markets and knowledge of the benefits of diverse diets, poor households may simply be unable to afford nutritionally rich foods (Warren and Frongillo 2017).

Ethiopia remains widespread (CSA and ICF International 2017). Moreover, Ethiopian children consume one of the least diverse diets in sub-Saharan Africa (Hirvonen 2016). At the household level, food consumption baskets are dominated by cereals and pulses, while the consumption of animal-source foods and micronutrient-rich fruits and vegetables is rare, especially in rural areas (e.g., Worku et al. 2016; Hirvonen et al. 2016). Such monotonous diets are regarded as a major contributor to malnutrition as well as to the incidence of non-communicable diseases in Ethiopia (Melaku et al. 2016).[3]

We analyze the evolution in prices of different food groups in Ethiopia using large-scale nationally-representative price datasets. We find that prices of nutritious foods and, consequently, their affordability has significantly worsened over the period 2007 to 2016: The prices of nutritious foods increased by between 19 and 62 percent over the decade studied. We then analyze the determinants of the observed trends in food prices, relying on time series analyses. We find that prices of nutritionally-rich food groups – compared to cereals – are relatively less affected by international prices, but more by rapidly increasing local and city demand. This increased demand is due to rapid income growth and increasing urbanization and the high-income elasticities for nutritious foods in Ethiopia. Moreover, we find that local production changes affected prices little, but national price rises were found to have been significantly linked with prices in commercial clusters in the country. Real exchange depreciations in our analysis are also shown to have larger impacts for cereals than for nutritious foods. Changes in transaction costs – fuel and transport costs – explained relatively little in price changes for any crop.

Our results have a number of implications.

- Given the large influence of prices on consumer choices of food in countries like Ethiopia, more investments and attention to the local production of nutritious foods is needed to reduce the prices of such foods and improve their affordability for consumers. Focus should not only be on production by the household itself – e.g., households might not have access to appropriate water supplies, shown to be an important determinant of the successful adoption of vegetable homestead gardening (Hirvonen and Headey 2018) – or in the locality in which they live, but more importantly on production in commercial clusters with comparative advantages in the production of such nutritious crops.
- Not only local production of food should be examined. Market and trade policies also play a role in improving affordability. The effects of exchange rate changes on agricultural commodity prices are found for all crops, given a number of indirect effects of these rate changes through the costs of intermediary inputs such as chemical fertilizers, agro-chemicals, and improved feed ingredients. However, the overvalued exchange rates that have been in vogue in Ethiopia over the last decade have kept food prices lower for cereals than for nutritious foods. An exchange rate policy more in line with market forces might therefore change relative food prices in favor of nutritious foods.
- Price controls for those foods that are traditionally associated with obesity should be relaxed so as to better reflect the true costs of these items. While obesity is less of an issue in Ethiopia than in other countries it is an emerging public health problem (Gebru et al. 2018).

[3] Recent research in Ethiopia suggests that the poor dietary diversity in rural areas can be explained, at least partly, both by limited knowledge about the health benefits of diverse diets and by poor access to food markets. Households in areas in which food crop production is not very diverse but which have good access to markets are found to have more diverse diets than do households in areas with similar production patterns but with poor access to markets and, so, depend primarily on own-production for the food they consume (Hoddinott, Headey, and Dereje 2015; Abebe, Haki, and Baye 2016; Kim et al. 2016; Zerfu, Umeta, and Baye 2016; Hirvonen and Hoddinott 2017; Hirvonen et al. 2017; Stifel and Minten 2017; Abay and Hirvonen 2017).

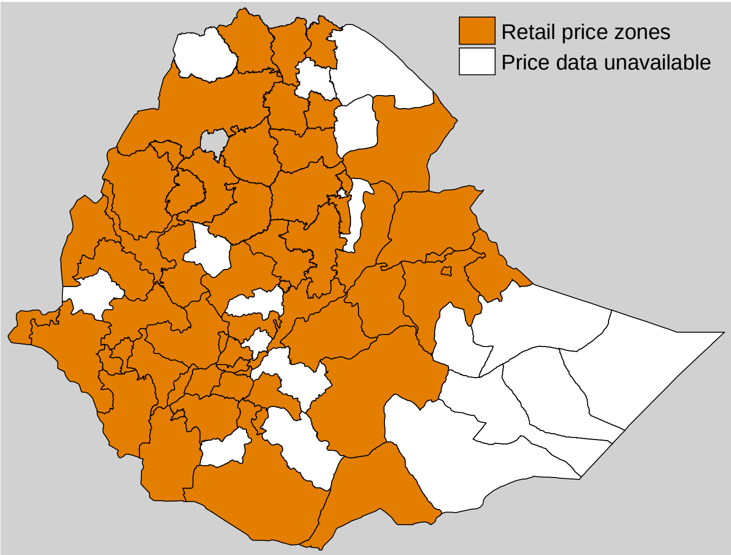
The remainder of this paper is organized as follows. The following section describes the data used for the descriptive analyses and discusses observed trends in prices of nutritious foods. Section 3 describes the data and methodology used in the econometric analyses and presents findings of the analyses. Section 4 concludes.

2. TRENDS IN PRICES OF NUTRITIOUS FOODS

2.1. Data

We use monthly price data for the period between January 2007 and December 2016 collected by the Central Statistical Agency (CSA) of Ethiopia under its periodic Consumer Price Survey. Prices are collected from 116 markets in all regions (but not in all zones) of Ethiopia. CSA enumerators – who reside permanently near these markets – collect price data from traders, retailers, and consumers. The number of surveyed markets in each region is approximately proportional to the region's share of the total urban population to ensure a sufficient degree of national representativeness (Figure 2.1). To assure comparability of prices over time and to remove the effect of general inflation on prices, we compute real prices by deflating nominal prices observed in the markets using the regional General Consumer Price Index (CPI), calculated by CSA, in order to express all prices in December 2011 birr terms (CSA 2017). This means that the prices reported here are relative to the price of the average consumption basket for the country.

Figure 2.1: Administrative zones of Ethiopia from which retail price data is collected by the Central Statistical Agency



Source: Authors' mapping based on CSA data.

Dietary quality is often proxied by dietary diversity. The literature typically adopts different numbers of food groups to measure dietary diversity for different demographic groups.[4] The common feature of these approaches is to group food items according to the key nutrients they provide. Following this approach, we study the price evolution of ten different food groups: grains, roots, and tubers; legumes and nuts; dairy products (milk, yogurt, cheese); eggs; flesh foods and small animal protein; vitamin A-rich dark green leafy vegetables; other vitamin A-rich vegetables and fruits; other fruits and vegetables; oils and fats; sugar and honey (Table 2.1). Households or individuals regularly consuming foods from a greater number of these food groups are likely to meet

[4] For example, WHO (2008) recommends a 7-food group indicator for children 6-24 months of age. FAO and USAID's Food and Nutrition Technical Assistance III Project (FANTA) proposes a 10-food group indicator to assess women's dietary diversity (FAO and FHI360 2016) and a 12-food group indicator for household level analysis (Swindale and Bilinsky 2006).

their needs in terms of both macro (e.g., carbohydrates, protein) and micro-nutrients (e.g. vitamin A, iron, zinc).

We use the 2011 Household and Consumption Expenditures Survey (HCES) data to identify the food items in each food group and to compute the average share of each item in the total weight (100 percent) of per capita consumption of each food group at the administrative zone level.[5] Table 2.1 lists the number of items in each food group in the HCES data (column 2) and those with price information in the CSA dataset (column 3).

Table 2.1: Descriptive statistics of data for the ten food groups used in the analysis of trends in the prices of nutritious foods

Food group	Items in HCES consumption data, number	Items with retail price data from the Consumer Price Survey, number	Share of total weight of items with price data, %
Grains, roots, and tubers	70	34	76.0
Legumes and nuts	52	28	83.8
Dairy products	9	5	72.6
Eggs	2	1	94.7
Flesh foods and small animal protein	15	7	97.0
Vitamin A-rich dark green leafy vegetables	4	3	97.6
Other vitamin A-rich vegetables and fruits	9	6	86.5
Other fruits & vegetables	33	15	89.7
Oils and fats	11	5	86.5
Sugar and honey	6	2	58.3
All food groups	211	106	82.9

Source: Authors' analysis of Consumer Price Survey and Household and Consumption Expenditures Survey (HCES) data.
Note: Column 4 shows the share by weight of total foods in each food group reported to be consumed in the HCES dataset and for which prices are available in the Consumer Price Survey dataset.

Then, for each of the ten food groups we calculate a weighted average price.[6] This average price considers the consumption share (importance) of each item in each food group. Out of the 211 items in all food groups (Table 2.1, column 2, last row), price information is available for only about half (106) of the items (column 3). Nevertheless, the price data include the most commonly consumed items that account for a larger share of the total weight in each food group (column 4). For instance, although price data are available for only indigenous hens' eggs, the other item in this food group, hybrid hens' eggs, accounted for less than 6 percent of the consumption of eggs. Table 2.1 shows that, overall, we can account for the price evolution of 83 percent of the average consumption basket (column 4, last row).

While we expect rural and urban prices to be highly correlated within zones, we conduct the same analysis using producer prices from rural markets. Although the producer price data have wider coverage of nearly 2,100 rural markets, they include prices only for primary crop and livestock outputs produced in each locality and exclude all processed or semi-processed food items. As a result, they are not representative of all foods consumed by rural households. To compensate for the lack of producer price data for a large number of processed items, we use zonal average retail prices for such food items.

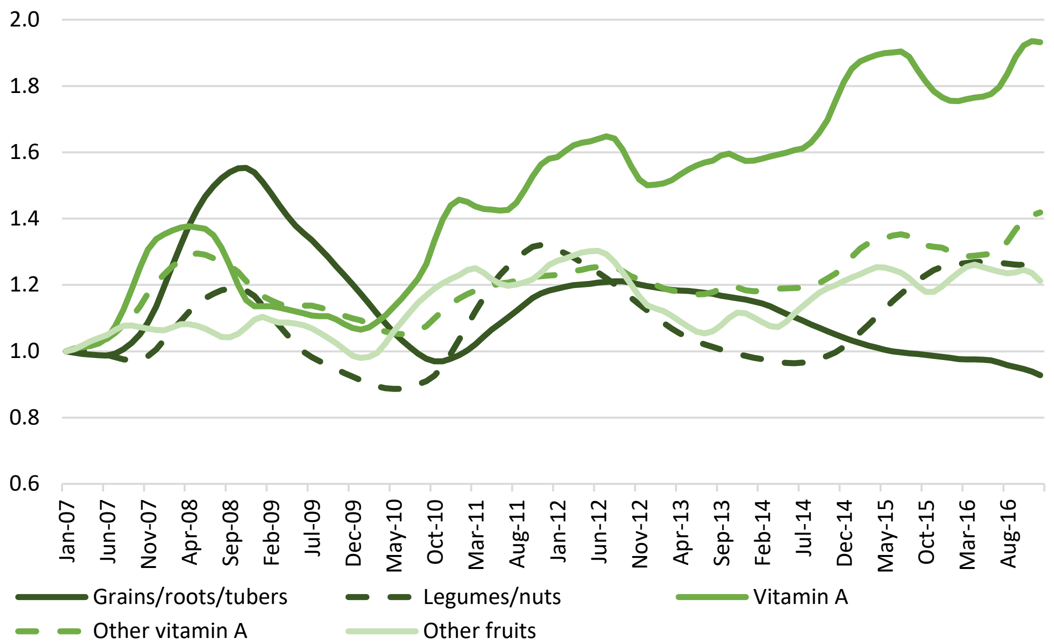
[5] HCES is the official source of poverty statistics in Ethiopia.

[6] For more information on the construction of prices indices, see Deaton and Tarozzi (2000).

2.2. Trends in prices of nutritious foods

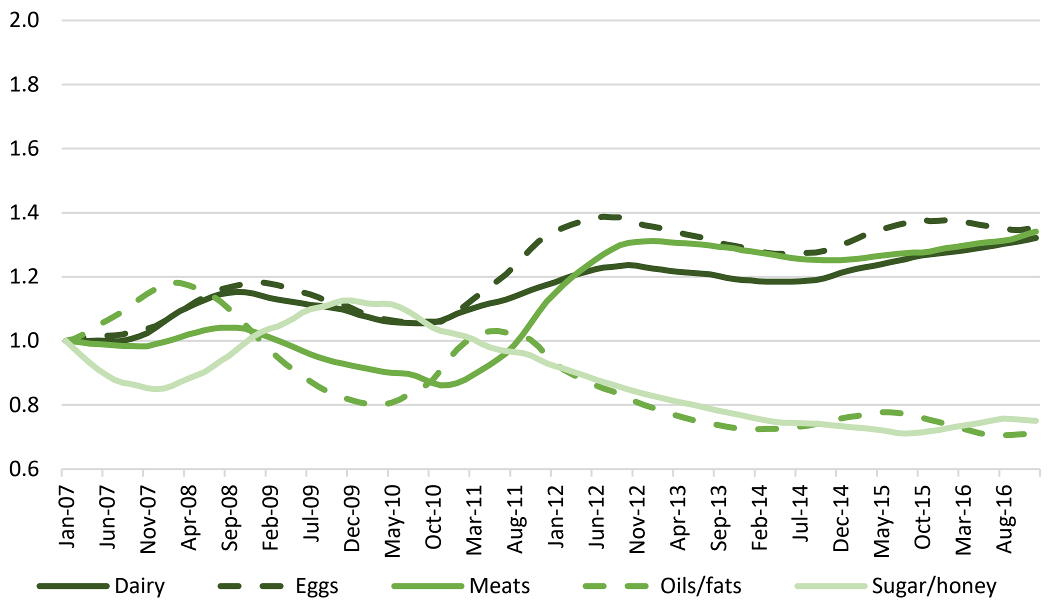
Figures 2.2 and 2.3 depict how the real consumer prices of different food groups have changed over the decade of study in Ethiopia. Figure 2.2 shows price trends for plant-based foods, while Figure 2.3 shows price trends for animal-source foods, oils and fats, and sugar and honey. All price indices are set to 1.0 in January 2007, the first month in the price data series used here. Price index values above 1.0 mean that real prices for foods in that food group increased in aggregate, while values below 1.0 imply that foods in the food group have become cheaper over time in real terms.

Figure 2.2: Real consumer price trends of plant-based foods in Ethiopia, 2007 through 2017



Source: Authors' analysis of Consumer Price Survey and Household and Consumption Expenditures Survey data

Figure 2.3: Real consumer price trends of animal-source foods, oils and fats, and sweeteners in Ethiopia, 2007 through 2017



Source: Authors' analysis of Consumer Price Survey and Household and Consumption Expenditures Survey data

Figures 2.1 and 2.2 and Table 2.2 show that prices of seven out of the ten food groups increased over the last decade. The largest price increases are observed for Vitamin A-rich dark green leafy vegetables – real prices of this food group increased by over 90 percent between January 2007 and December 2016 (Figure 2.2). Prices of foods in the vitamin A-rich fruits and vegetables group increased by 40 percent, while prices of other fruits and vegetables increased by over 20 percent over the same period. The price index for legumes and nuts displayed considerable volatility over the last decade – real prices of legumes and nuts were slightly lower in mid-2014 than in January 2007, but by December 2016 they were 26 percent higher.

Table 2.2: Evolution of retail and producer prices, by food group, percentage total change in real prices between 2007 and 2016

Food group	Urban retail prices	Rural producer prices
Grains, roots, and tubers	-2.3	-2.4
Legumes and nuts	26.2	24.5
Dairy products	26.9	39.2
Eggs	34.1	41.0
Flesh foods and small animal protein	33.4	15.4
Vitamin A-rich dark green leafy vegetables	61.9	11.4
Other Vitamin A-rich vegetables and fruits	18.8	3.0
Other fruits and vegetables	22.0	-0.3
Oils and fats	-35.2	-36.3
Sugar and honey	-23.6	-19.1

Source: Authors' analyses of Consumer Price Survey and Rural Producer Price data.
Note: Percentage change computed using average annual real prices of items in 2016 and 2007

From Figure 2.2, we see that the prices of all animal-source food categories also increased substantially. The real prices of dairy, eggs, and meat increased by over 32 percent over the decade between 2007 and 2016. This increase is in contrast with the real prices of grains, roots, and tubers, important components of the total consumption basket, which at the end of 2016 were at the same level as at the beginning of 2007.[7] A similar pattern of lower prices at the end of the study period than at the beginning is also seen for the oils and fats and sugar and honey food groups. However, the persistent increase in prices of the remaining food groups is worrisome since the consumption of these food groups – many of which are rich in protein and in micronutrients that are not available in foods of the three food groups showing stable to lower prices – is low in many parts of Ethiopia.

We also examined changes in prices of food groups traditionally associated with rising obesity (Popkin, Adair, and Ng 2012), namely oils and fats and sugar and honey. While obesity is less of an issue in Ethiopia than in other countries, it is an emerging problem with 6 percent of adult women nationally and 15 percent in urban areas being overweight or obese (CSA and ICF International 2012). Related, an increasing number of Ethiopians are struggling with high blood pressure and diabetes (FMoH/UNICEF/ EU 2016). We find that prices of sugar and honey decreased by 24 percent over the last decade, while oils and fats decreased by 35 percent (Table 2.2), a worrying trend.

Finally, in the last column of Table 2.2 we provide the results from the rural producer price data, augmented with retail prices of mainly processed items. These results are qualitatively similar with

[7] Prices of grains, tubers, and roots were higher in 2008 and 2009, and again in 2011, possibly linked to the international food price crisis. However, over the entire period between 2007 and 2016, grains, tubers, and roots prices were 14 percent higher in an average month relative to January 2007 prices. However, this was less than the corresponding price levels for all food groups, except oils and fats, sugar and honey, and legumes and nuts.

Moreover, between July 2015 and December 2016, the last 18 months of the period studied, real prices for grains, tubers, and roots were lower than the prices for this food group at the beginning of the study period in 2007.

those obtained from the retail price data with two exceptions. First, increases in prices of animal-source foods items, except for meats, are higher in the producer price data. Second, prices of ‘other fruits’ remained about the same. Overall, increases in prices of most crop items are relatively smaller in this second price series.

3. DETERMINANTS OF FOOD PRICE CHANGES

3.1. Data

The econometric analyses study factors associated with the real retail prices of 14 of the 106 food items for which prices are collected in the Consumer Price Survey (Table 2.1). The items were selected based on the availability of retail prices, which are used as dependent variables in the analyses, and the importance (share) of the items in their food group. The 14 items represent all ten food groups listed in Table 2.1 except for “Other vitamin A-rich vegetables and fruits”, which are excluded from the analyses due to having only intermittent price data. The items selected from the remaining nine food groups are:

1. Grains, roots and tubers: teff, maize, and wheat;
2. Legumes and nuts: field peas and horse beans;
3. Dairy products: milk;
4. Eggs;
5. Flesh foods and small animal protein: beef;
6. Vitamin A-rich dark green leafy vegetables: kale;
7. Other fruits and vegetables: onion, bananas, and tomatoes;
8. Oils and fats: cooking oil;
9. Sugar and honey: sugar.

A graph of the price evolution of these different foods is shown in Annex 1.

The econometric analyses are conducted using administrative zone-level aggregated data. Our empirical methodology mostly follows the one implemented by Shively and Thapa (2016) for Nepal where they use a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) methodology to model local rice and wheat prices as a function of different explanatory variables.

We now discuss the different variables included in our estimated models. First, access to infrastructure and proximity to markets influence the flow of food to and from a given locality and, thus, are important determinants of food prices in the locality. We assume that local real food prices are associated with the density and quality of roads serving the locality and its proximity to urban centers. We account for this factor using a variable, travel time, which is constructed using district level data on the length and type/quality of roads and the distance between the center of each district to an urban center with population of 50,000 or higher. Out of the ten years, 2006 to 2015, covered in the analyses, data on roads are available for three – 2007, 2010, and 2015. Consequently, travel time is calculated for the three years and linearly estimated for the remaining years. Food prices are also assumed to be associated with transportation costs. Monthly retail fuel/diesel price data collected through CSA’s Consumer Price Surveys are used to proxy transportation costs.

Second, prices of a given item are associated with the supply of the item in the locality. We account for this factor by using per capita output of the item in the zone. However, given output levels can both influence and be influenced by prices, i.e., they are endogenous, we use the predicted value of outputs to compute per capita output. Following Shively and Thapa (2016), in the regression analyses conducted to predict each crop output, we use as independent variables the area of the crop cultivated, the number of farmers producing the crop, the quantity of rainfall during the crop season, and zonal and period dummies. Similarly, in the regression analyses used to predict animal-source foods production, we use the animal stock used in the production of the item, the number of farmers producing the item, and zonal and period dummies as independent variables.

Third, food prices are expected to increase with increases in demand for the item. We use the population density per total crop area in each zone as a measure for food demand.

Fourth, a large majority of the cities and towns from which the retail price data are collected are connected with Addis Ababa, the capital and by far the largest city of Ethiopia, where almost 40 percent of the urban population of the country resides (Schmidt et al. 2018). Therefore, prices in Addis Ababa are assumed to be important determinants of prices for each locality and are used as an explanatory variable in the food price equations.

Fifth, Ethiopia conducts formal cross-boundary trade with Djibouti, Kenya, Somalia, Somaliland (Northern Somalia), South Sudan, and Sudan. Moreover, anecdotal evidence indicates that considerable informal trade also is conducted with these countries. Traders collect food items and livestock destined for these countries from many areas of Ethiopia. As a result, local prices of the items considered in the analyses are expected to be associated with the prices of the items in these countries. We proxy the prices in the neighboring countries by constructing average prices of the items in districts bordering the six neighboring countries listed.

Sixth, Ethiopia has diverse cropping systems, and different districts focus on the production of different food items depending, among others, on climate, the food culture, and the productivity of the area. The prices of food items in general are assumed to be associated specifically with the prices of those items in areas with a comparative advantage for their production. To account for this effect, we use as explanatory variable the average price of each item in high productivity areas and refer to these prices as the commercial cluster price.[8]

Seventh, exchange rate movements are related to overall levels of food prices, be it tradables or non-tradables (Krueger et al. 1988, Barrett 1997). We account for this influence on local food prices using the real exchange rate of the birr to the U.S. dollar.

Finally, the price of a given food item in a given month closely follows the price of the same item in the previous month. We assume therefore that the real price of each food item is associated with its own lagged values.

3.2. Regression methods

Given the foregoing discussion, the real price of a given food item can be expressed as:

$$P_{ijt} = \alpha_{i0} + \gamma_i P_{ijt-1} + \sum_{l=0}^{1} \beta_{iat-l} P_{iat-l} + \sum_{l=0}^{1} \beta_{ibt-l} P_{ibt-l} + \sum_{l=0}^{1} \beta_{iht-l} P_{iht-l} + \vartheta_i E_t + \delta_{iF} F_{jt} + \delta_{iA} A_{jt} + \delta_{iD} D_{jt} + \delta_{iO} O_{ijt} + \theta_{i1} T + \theta_{i2} M + \theta_{i3} Y + \theta_{i4} L + \mu_{ijt} \quad (1)$$

where P_{ijt} is the real price of item i in market j and month t; P_{ikt} is the real price of i in Addis Ababa (k=a); boundary markets (k=b), and high productivity area markets (k=h). E_t stands for the exchange rate, F_{jt} for fuel/diesel prices in market j, A_{jt} for travel time, D_{jt} for population density, and O_{ijt} for per capita output of item i in j. Included in equation (1) are also time trend (T) and

[8] The average price is constructed from prices of the 30 districts with the highest average productivity of the food item during the period considered.

month/seasonality (M), year (Y), and location/region (L) dummy variables. μ_{ijt} is an identically and independently distributed error term. α_{i0}, γ_i, β_{ik}, ϑ_i, δ_{in}, and θ_{is} are parameters to be estimated.

To ease interpretation, we calculate short- and long-run elasticities as done by, for example, Barrett (1997) and Bachewe and Taffesse (2017). The long-run elasticity of real prices with respect to an explanatory variable, for instance Addis Ababa prices, is given by $((\beta_{iat} + \beta_{iat-1})/(1-\gamma_i)) * \frac{\bar{P}_{ia}}{\bar{P}_i}$; where β_{iat} and β_{iat-1} are estimates of contemporaneous and lagged Addis Ababa market price, respectively; γ_i is the estimate of lagged dependent variable, and $\bar{P}_{ia}$ and $\bar{P}_i$ are mean values of Addis Ababa market prices and real price of item i (Bachewe and Taffesse 2017). The short run elasticity of, for instance, the real exchange rate, is given by: $\vartheta_i * \frac{\bar{E}}{\bar{P}_i}$; where ϑ_i is the estimate of the real exchange rate and $\bar{E}$ is the mean value of real exchange rate.

Diagnostic tests conducted on the data reveal that the data exhibit a first-order autoregressive conditional heteroskedasticity (Annex 2). Given this result, estimating equation (1) using ordinary least squares (OLS) can distort standard errors and lead to erroneous statistical inferences. Efficiency gains can be made if the price equations are estimated using an Autoregressive Conditionally Heteroskedastic (ARCH) model (Shively and Thapa 2016), whereby parameters of the mean price equation (1) are estimated simultaneously with parameters of the variance equation. The variance equation is given as:

$$\sigma_{ijt}^2 = \gamma_{i0} + \gamma_{i1}\epsilon_{ijt-1}^2 + \sum_{l=0}^{1}\gamma_{ia}P_{iat-1} + \sum_{l=0}^{1}\gamma_{ib}P_{ibt-1} + \sum_{l=0}^{1}\gamma_{ih}P_{iht-1} + \lambda_{iE}E_t + \lambda_{iF}F_{it} + \lambda_{iA}A_{it} + \lambda_{iO}O_{it} + \lambda_{iD}D_{it} + \eta_{i1}T + \eta_{i4}L + \xi_{ijt} \quad (2)$$

where γ_{is}, λ_{it}, and η_{iu} are parameters to be estimated and ξ_{ijt} are assumed to be mean-zero independently and identically distributed error terms. If $\gamma_{i1} = 0$, then there are no dynamics in the conditional variance equation, i.e., there are no ARCH effects. In equation (2) the variances of the regression disturbances (σ_{ijt}^2) are expressed as a function of the size of prior unanticipated innovations (ϵ_{ilt-1}^2) and factors expected to influence food price variances. In addition to the ARCH model, we estimate and compare performances of three more general ARCH models.

The Generalized Autoregressive Conditionally Heteroskedastic (GARCH) model, adds lagged conditional variances (σ_{ijt-1}^2) to equation (2) and is specified as:

$$\sigma_{ijt}^2 = \gamma_{i0} + \gamma_{i1}\epsilon_{ijt-1}^2 + \beta_{i1}\sigma_{ijt-1}^2 + \sum_{l=0}^{1}\gamma_{ia}P_{iat-1} + \sum_{l=0}^{1}\gamma_{ib}P_{ibt-1} + \sum_{l=0}^{1}\gamma_{ih}P_{iht-1} + \lambda_{iE}E_t + \lambda_{iF}F_{it} + \lambda_{iA}A_{it} + \lambda_{iO}O_{it} + \lambda_{iD}D_{it} + \eta_{i1}T + \eta_{i4}L + \xi_{ijt} \quad (3)$$

In equation (3), the condition $\gamma_{i1} + \beta_{i1} < 1$ guarantees covariance stationarity for each panel member.

One of the shortcomings of the GARCH model is that it assumes price volatility to respond symmetrically to negative and positive shocks. This assumption may not necessarily hold. Among models that allow for price volatility to behave asymmetrically to positive and negative shocks, we estimate the asymmetric GARCH (AGARCH) and threshold GARCH (TGARCH) models. The AGARCH model is specified as:

$$\sigma_{ijt}^2 = \gamma_{i0} + \gamma_{i1}\epsilon_{ijt-1}^2 + \gamma_{i2}\epsilon_{ijt-1} + \beta_{i1}\sigma_{ijt-1}^2 + \sum_{l=0}^{1}\gamma_{ia}P_{iat-1} + \cdots + \xi_{ijt} \quad (4)$$

where $\gamma_{i2} > 0$ implies that positive shocks result in larger increases in price volatility than negative shocks of the same absolute magnitude. The TGARCH model is specified as:

$$\sigma^2_{ijt} = \gamma_{i0} + \gamma_{i1}\epsilon^2_{ijt-1} + \gamma_{i2}|I_{(\epsilon_{ijt-1}>0)}\epsilon^2_{ijt-1} + \beta_{i1}\sigma^2_{ijt-1} + \sum\nolimits_{l=0}^{1}\gamma_{ia}P_{iat-1} + \cdots + \xi_{ijt} \quad (5)$$

In equation (5), the indicator function $I_{(\epsilon_{ijt-1}>0)}$ is 1 if $\epsilon_{ijt-1} > 0$, and 0 if $\epsilon_{ijt-1} < 0$. Positive values of γ_{i2} indicate that positive shocks have larger effects on price volatility than do negative shocks.

3.3. Estimation issues

In our empirical analyses, we estimate the price equations for three sets of items. The first equation is based on three items from the "Grains, roots, and tubers" food group – maize, teff, and wheat. These cereals constitute the major staple foods in most parts of the country and are among the foods with the highest share in total per capita consumption expenditure.[9] The second equation combines nine food items, which are considered nutritious but are often consumed by Ethiopian households in small quantities. These items saw a marked increase in prices over the decade studied as shown in the previous section. The third equation combines cooking oil and sugar. Being largely manufactured items, zonally disaggregated output data are not available for these food items. Consequently, they could not be analyzed together with the other food items as output-related variables needed in the analyses are not available for them. In all equations, the food items are represented by dummy variables. We also include a separate dummy variable for animal-source food items in the second equation for nutritious foods.

We include three additional variables in the price equations to test to what extent real prices of tradable and non-tradable items are differently associated with variables representing international trade and local production. The research literature on trade (e.g., Armington 1969) shows that differential effects should be expected. We categorize teff, bananas, kale, tomatoes, milk, and eggs as non-tradable items. Teff, although an important staple food, is largely consumed only in Ethiopia and was legally prohibited from being exported for most of the period studied.

We used standard routines in Stata to estimate the real price equations using all five econometric specifications discussed in section 3.2. We compare the performance of the three specifications using a log-likelihood ratio test and the Akaike Information Criterion (AIC) (Annex 3) and present results for the specification with the superior performance. Estimates of coefficients for the three price equations were mostly significant and consistent with what was expected a priori for their effects (Table 3.1). Moreover, estimates of the 14 item-specific equations were also done and they mostly have similar implications to the results presented in Table 3.1.[10] In Table 3.2 we provide estimated short-run and long-run elasticities of real prices with respect to each of the explanatory variables. Estimates of the contributions of each factor to price changes in the last decade are presented in Table 3.3.

3.4. Results of econometric analyses: Mean equation

The following observations can be made about the results of the mean price equation. First, local demand and production conditions play an important role in the formation of prices of food items. The estimates of the coefficients on lagged prices vary between 0.82 and 0.87 for the three equations (Table 3.1). This indicates the persistence of past prices for current price formation. Local supply of the items, measured in terms of output per capita, is, as expected, negatively associated with real prices. The estimated elasticities for the cereals group imply a 16 (11) percent decline in prices of non-tradables (tradables) for a doubling of per capita output, while the short-run elasticity is small at 2 and 3 percent for tradables and non-tradables, respectively (Table 3.2). The estimate of

[9] In 2011, the average per capita consumption spending on maize was highest out of the145 items in HCES dataset. Spending on teff was second highest, while average spending on wheat ranked fifth. These three cereals accounted for a quarter of the consumption spending of an average individual.

[10] Estimates from the regression models not presented in the paper can be obtained upon request.

output per capita is also significant and has the expected sign in the price equations of nutritious foods. However, their effect is small, suggesting that prices of these nutritious foods are less affected by local zonal production levels. This is consistent with the findings of Sibhatu and Qaim (2017) who show that Ethiopian consumers rely significantly more on markets to obtain nutritious foods (with milk being the exception) than they do to obtain cereals.[11]

Table 3.1: Determinants of food prices, mean equation

	Cereals (GARCH)		Nutritious items (AGARCH)		Cooking oil and sugar (TGARCH)	
Variable	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**
Local retail price (t-1)	0.816***	0.004	0.849***	0.002	0.868***	0.003
Commercial cluster price	0.167***	0.008	0.250***	0.006	-	-
Commercial cluster price (t-1)	-0.067***	0.009	-0.189***	0.006	-	-
Addis Ababa retail price	0.469***	0.022	0.318***	0.007	0.442***	0.007
Addis Ababa retail price (t-1)	-0.464***	0.014	-0.261***	0.007	-0.323***	0.007
Border price	0.138***	0.020	0.147***	0.007	0.174***	0.009
Border price (t-1)	-0.108***	0.013	-0.133***	0.006	-0.158***	0.008
Border price*tradable dummy	0.060***	0.020	0.023***	0.006	-	-
Mean travel time	0.003*	0.002	-0.007***	0.001	0.006***	0.001
Fuel price (birr/liter)	0.012***	0.004	0.016***	0.005	-0.030***	0.004
Population per total crop area (number/km^2)	0.006***	0.001	0.002**	0.001	0.001	0.001
Per capita output (kg)	-0.003***	0.000	-0.003***	0.000	-	-
Per capita output*non-tradable dummy	-0.001***	0.001	-0.002***	0.001	-	-
Real monthly exchange rate (birr/USD)	0.026**	0.012	0.040***	0.012	0.091***	0.008
Exchange rate*tradable dummy	0.012	0.009	0.012**	0.006	-	-
Time trend (monthly)	0.0002***	0.0001	0.000***	0.000	0.0004***	0.000
Animal-source food dummy (0/1)	-	-	-0.007	0.007	-	-
Constant	-0.096***	0.036	-0.233***	0.039	-0.221***	0.024
Seasonality (month) dummies	Yes		Yes		Yes	
Year dummies	Yes		Yes		Yes	
Region dummies	Yes		Yes		Yes	
Item dummies	Yes		Yes		Yes	

Source: Authors' analyses. GARCH = Generalized Autoregressive Conditional Heteroskedasticity model; AGARCH = Asymmetric GARCH; TGARCH = Threshold GARCH;
Note: Estimates with superscripts ***, **, and * are significant at 1%, 5%, and 10% levels of significance.

[11] However, this result might also be an indication of problems in the accurate measurement of the production of nutritious crops. Belg production data and production from irrigated areas, where a number of the vegetables included in our analysis are grown, are not thoroughly collected by CSA. This issue in the data deserves further research.

Table 3.2: Estimates of short-run and long-run elasticities of real retail prices[12]

Variable	Cereals		Nutritious items		Cooking oil and sugar	
	Short-run	Long-run	Short-run	Long-run	Short-run	Long-run
Commercial cluster price	0.16	0.52	0.27	0.44	-	-
Addis Ababa retail price	0.54	0.03	0.36	0.42	0.40	0.81
Mean travel time	0.002	0.01	-0.002	-0.01	0.001	0.01
Fuel price	0.03	0.15	0.02	0.10	-0.02	-0.17
Population density	0.11	0.62	0.13	0.88	0.04	0.34
Border price						
Non-tradable	0.16	0.18	0.17	0.11		
Tradable	0.23	0.56	0.20	0.29	0.18	0.12
Per capita output						
Non-tradable	-0.03	-0.16	-0.005	-0.03		
Tradable	-0.02	-0.11	-0.003	-0.02	-	-
Real exchange rate						
Non-tradable	0.06	0.33	0.04	0.27		
Tradable	0.09	0.49	0.05	0.35	0.07	0.53

Source: Authors' analyses

Second, the elasticity of population density indicates that local prices are highly associated with local demand conditions for cereals, nutritious foods, and manufactured cooking oil and sugar. Comparison of the estimates of the three equations indicates that prices of agricultural items, which mostly are produced locally, are more strongly associated with local demand conditions than are the prices of cooking oil and sugar, which are mostly transported from other areas and are influenced by government subsidy and supply conditions.[13]

Third, food prices are influenced by prices in Addis Ababa and in commercial clusters. The estimate of the coefficient on the Addis Ababa market price is the highest after the lagged dependent variable and the estimated elasticity on this coefficient is among the highest in all equations, indicating the important association of this central market with local prices.[14] Prices for both cereals and nutritious foods are also strongly associated with commercial cluster prices.

Fourth, local prices are also importantly associated with international markets. Estimated short-run elasticities of agricultural items with border prices are about 0.2, indicating the considerable association in the short-run between prices in neighbouring countries and local prices. However, long-run elasticities are significantly higher for cereals compared to nutritious foods, indicating that the prices for nutritious foods are more formed through national conditions. Exchange rate depreciations – more Birr being exchanged for the dollar – lead to increases in the prices of local foods, as shown by the significant positive coefficients. Elasticities are higher for cereals than for

[12] The long-run and short-run elasticities of real food prices with respect to the three dependent variables that are interacted with tradable/non-tradable dummy variable involve the estimate of the interaction term. Accordingly, the long-run elasticity of real prices with respect to border prices of tradable items is given by $((\beta_{ibt} + \beta_{ibt-1} + \rho_i)/(1 - \gamma_i)) * \frac{\bar{P}_{ib}}{\bar{P}_i}$; where β_{ibt} and β_{ibt-1} are estimates of contemporaneous and lagged border market price, respectively; $\bar{P}_{ib}$ is the mean value of border market prices; and ρ_i is the estimate of the interaction of border prices and tradable dummy. In contrast, the long-run elasticity of real prices with respect to border prices of non-tradable items excludes ρ_i from the sum in the first parentheses. Similarly, the short-run elasticity of real price with respect to per capita output of non-tradable items is given by $(\delta_{iO} + \varphi_i) * \frac{\bar{O}_i}{\bar{P}_i}$; where δ_{iO} is the estimate of per capita output; $\bar{O}_i$ is mean per capita output of item i; and φ_i is the estimate of the interaction of per capita output and non-tradable dummy.

[13] The price decreases for these latter products might be related with price settings and market control by the government. Sugar production and imports in the country is monopolized by the Sugar Corporation Enterprise. Palmoil, the most common commercial brand of cooking oil in the country, is imported by the government and often distributed through its *kebele* shops at subsidized prices (Assefa et al. 2016).

[14] This is line with findings from Baffes et al. (2017) in Tanzania where they show the large influence of the city of Nairobi in neighboring Kenya on local maize prices.

nutritious foods, again indicating that the prices of cereals are more affected by international trade factors than are the prices for nutritious foods.[15]

Fifth, the tradability of a food item shows a differential price formation, as expected a priori. The interaction term between per capita output and a non-tradable dummy variable indicates that elasticities of local price with respect to output per capita are higher for non-tradables than for tradables. The estimate of the coefficient for the real exchange rate and its interaction term with a tradable dummy indicates the more important association of local prices of tradables with international trade. However, non-tradables are affected in an important way as well, likely through the effects of the costs of intermediary inputs to their production. Moreover, the estimate of the interaction of border prices with a tradable dummy variable indicates, as expected, that local prices of tradable items are influenced more by prices of the respective items in neighbouring countries.

Finally, transaction costs matter for local price formation. The estimate of mean travel time, a variable intended to gauge the effect on local prices of connectedness and computed by considering the length and quality of roads and the distance to towns with a population of 50,000 or higher, is negative and significant in the price equation for nutritious foods. The results indicate that prices of the items are lower in more remote areas, which often rely more on own agricultural production (Minten et al. 2016). However, we do not see that effect for cereals where it has been shown that there is significant national trade, with prices in cereal deficit areas significantly higher (Minten et al. 2014). The coefficient on this variable is positive and significant in the cooking oil and sugar equation, indicating the relatively higher price of these manufactured items in more remote areas, possibly because of lower distribution of cooking oil and sugar at the government fixed lower prices in those areas. The coefficient of fuel prices in the cereal and nutritious food equations further indicate that higher transportation costs are associated with higher prices of the items. The long-run elasticity for fuel prices varies between 0.10 and 0.15, lower than estimates of an elasticity of 0.34 found by Dillon and Barrett (2015) on the impact of global oil prices on Ethiopian maize prices. This lower estimate in our regressions might be explained by the relatively low price of maize in the cereal category and therefore the relatively higher importance of transport costs in the prices for this staple crop. Fuel prices have a wrong sign in the cooking oil and sugar equation, again likely indicating the impact of price setting by the government (Assefa et al. 2016).

While we estimated in the analysis above the link of the explanatory variables to local price changes, we did not examine their relative contribution to overall price changes over the period studied. This is important as, while elasticities might be high, the underlying factors might change very slowly. Consequently, they might have had little contribution to price increases or decreases over the period studied. In Table 3.3, we provide the results of this exercise to look at the contribution of different factors. We assess short-run contributions as the product of the short-run elasticity and the average annual change and long-run contributions as the product of the long-run elasticity and sum of annual changes in factors.

[15] Dillon and Barrett (2015) found an exchange rate elasticity in Ethiopia for maize of 0.19. The argue that the effect of exchange rate was lower as in other Eastern African countries as Ethiopia's maize prices more closely followed global maize prices.

Table 3.3: Contribution of factors to change in real retail prices, 2007 to 2016

Variables	Cereals		Nutritious items		Cooking oil & sugar	
	Short-run	Long-run	Short-run	Long-run	Short-run	Long-run
Commercial cluster price	0.004	0.123	0.008	0.111	-	-
Addis Ababa retail price	0.015	0.007	0.012	0.133	-0.030	-0.552
Mean travel time	-0.0001	-0.007	0.0001	0.008	-0.0001	-0.006
Fuel price	-0.001	-0.046	-0.001	-0.032	0.001	0.052
Population density	0.003	0.127	0.003	0.157	0.002	0.112
Border prices						
Non-tradable	0.001	0.006	0.004	0.026	-	-
Tradable	0.007	0.154	0.007	0.094	-0.008	-0.048
Per capita output						
Non-tradable	-0.002	-0.074	-0.001	-0.059	-	-
Tradable	-0.001	-0.040	-0.001	-0.032	-	-
Real exchange rate						
Non-tradable	-0.003	-0.167	-0.002	-0.138	-	-
Tradable	-0.005	-0.249	-0.003	-0.178	-0.004	-0.271

Source: Authors' analyses
Note: Short-run contributions=short run elasticity*average annual change; long-run contributions=long-run elasticity*sum of annual changes in factor.

The results show that real exchange rate changes have contributed in an important way to keep local food prices low. Despite the positive effect of exchange rate devaluations on food prices (as shown in Table 3.2), the government relied on an increasingly overvalued exchange rate over the period considered (e.g., Moller 2015) and this policy had relatively more effect on cereals than on nutritious foods. We also see less contribution of international price changes on nutritious foods than for cereals. Local prices of nutritious food have shown large increases due to increasing local urban demand and a more urbanized Ethiopia (Schmidt et al. 2018) as seen in the large influence of the Addis Ababa prices. This likely is driven by increasing incomes in urban areas (World Bank 2014; 2019) and high-income elasticities for these nutritional foods (Tafere et al. 2010, Abegaz et al. 2018, Worku et al. 2017), thereby pulling prices up in the rest of the country. We further see important impacts of commercial cluster prices, for cereals as well as nutritious items. Local demand increases due to population and income growth have also contributed in an important way to price increases for both cereals and nutritious foods, but more so for the latter. Changes in transaction costs in the overall picture, despite large investments in road infrastructure, have mattered little over the period studied.

3.5. Results of econometric analyses: Variance equation and market integration

Estimates of the variance equation parameters associated with the estimates in Table 3.1 are presented in Table 3.4. The negative estimate of the asymmetric term in the nutritious items' equation implies that a positive price shock is correlated with a smaller increase in future price volatility than a negative price shock of the same magnitude. Conversely, the positive estimate of the threshold term in the cooking oil and sugar equation implies that a positive price shock is correlated with a larger increase in future price volatility. The mostly insignificant estimate of commercial cluster prices indicates that higher prices in these markets do not lead to higher variance in local market prices. Higher central market prices lead to lower variance of agricultural items, while the reverse holds for primary boundary prices. Increases in travel time lead to higher variability in prices of nutritious foods, as markets become more localized in such remote areas, while prices of cooking oil and sugar, which increase with travel time, show lower variability with remoteness. Higher fuel prices lead to higher variability of real prices for all, while increases in population density lead to lower variation in prices, possibly because of 'thicker' markets with more competition. Higher per capita output, which has a mean price reducing effect, leads to higher variation in prices.

Table 3.4: Determinants of food prices, variance equation

Variables	Cereals (AGARCH) Coefficient	Cereals (AGARCH) Standard error	Nutritious items (AGARCH) Coefficient	Nutritious items (AGARCH) Standard error	Cooking oil and sugar (TGARCH) Coefficient	Cooking oil and sugar (TGARCH) Standard error
Commercial cluster price (t-1)	-1.396*	0.818	0.057	0.071	-	-
Addis Ababa retail price (t-1)	-11.246***	1.831	-1.451***	0.090	3.764***	0.209
Primary boundary (t-1)	-3.834***	0.827	0.814***	0.083	-4.105***	0.239
Mean travel time	0.082	0.097	0.330***	0.014	-0.511***	0.017
Fuel price (birr/liter)	0.559*	0.301	0.441***	0.057	6.063***	0.153
Population per total crop area (number/km^2)	-0.306***	0.066	0.001	0.017	-0.546***	0.017
Per capita output (kgs)	0.108***	0.020	0.043***	0.005	-	-
Real exchange rate (birr/USD)	-9.491***	0.987	0.959***	0.133	-6.697***	0.241
Time trend (monthly)	-0.041***	0.003	0.005***	0.001	-0.013***	0.001
Constant	25.698***	3.245	-10.168***	0.481	0.504	0.741
L.ARCH	0.083***	0.002	0.165***	0.003	0.375***	0.014
L.GARCH	0.893***	0.002	0.738***	0.003	0.504***	0.006
L.AGARCH/L.TGARCH	-	-	-0.089***	0.008	0.329***	0.025
Log-Likelihood	22,578		34,457		19,415	
AIC	-45,024		-68,752		-38,712	
Observations	18,220		51,430		13,090	

Source: Authors' analyses. AGARCH = Asymmetric Generalized Autoregressive Conditional Heteroskedasticity model; TGARCH = Threshold Generalized Autoregressive Conditional Heteroskedasticity model.
Note: Estimates with superscripts ***, **, and * are significant at 1%, 5%, and 10% levels of significance.

Finally, we test the short- and long-run integration of markets (Table 3.5). The tests reject the null hypothesis that local markets are integrated with commercial cluster, Addis Ababa, and border markets in the short-run ($\beta_{ik} = 1\ \forall k$ and $\gamma_i = 0$) for all three price equations in Table 3.1. The null hypothesis of long-run market integration ($\gamma_i + \sum \beta_{ik} = 1$) is not rejected for the cooking oil and sugar equation in Table 3.1, while it is for the cereals and nutritious items equations, indicating important frictions in the marketing system.[16]

Table 3.5: Market integration tests

Equation	$Price_{t-1}=1$ Chi^2	$Price_{t-1}=1$ P-value	$\gamma_i+\beta_{ik}=1$ (long-run market integration) Chi^2	$\gamma_i+\beta_{ik}=1$ (long-run market integration) P-value	$\gamma_i=0$ and $\beta_{ik}=1\ \forall k$ (short-run market integration) Chi^2	$\gamma_i=0$ and $\beta_{ik}=1\ \forall k$ (short-run market integration) P-value
Cereals	2096.94	0.000	72.17	0.000	81618.8	0.000
Nutritious foods	81618.83	0.000	9.81	0.002	290000.0	0.000
Cooking oil and sugar	2385.01	0.000	0.62	0.430	140000.0	0.000

Source: Authors' analyses

4. CONCLUSIONS AND IMPLICATIONS

We study price patterns of different food groups in Ethiopia over the period 2007 to 2016. We find that prices of all food groups rich in macro- and micro-nutrients increased in real terms. At the same time, real prices of food groups that are associated with overweight and obesity (oils, fats, and

[16] Using price data from wholesale markets in Ethiopia, Minten et al. (2014) show rather good and improving market integration over time. However, the authors only assessed integration at the wholesale market level and only for cereals, which possibly explains the divergence with the results here.

sugar) decreased over the last decade. Similar patterns emerge when we use producer price data from rural areas instead of consumer prices. These trends confirm overall trends seen in recent years in developed countries and emerging economies of general increases in the costs of relatively healthier diets (Wiggins et al. 2015). These price movement patterns are important for nutrition in Ethiopia as prices of food are critically important for the food consumption decisions of low-income households, as is evident in consistently high estimates of food price elasticities of consumption.[17]

Our findings have a number of policy implications. The Ethiopian government has a good track record with respect to improvement of cereal production in the country in the last decade. This improvement has been driven by a focus on modernizing the agricultural sector and increased adoption of modern technologies (Bachewe et al. 2018). It has been shown that increased productivity and production in the cereal sector has brought about considerable improvements in poverty alleviation and in calorie intake (World Bank 2014). However, such a transformation has not been noted for the consumption of high-value nutritious foods (Bachewe et al. 2018b). As the Ethiopian economy continues to transform, high-value crops, such as fruits and vegetables and animal-source foods, which are consumed more frequently as income increases, i.e., they are income elastic, are critical to improving the quality of diets. However, current price trends for these foods will limit their accessibility to the poor.[18]

To reduce price levels, improve dietary quality, and ultimately impact nutritional and health outcomes in the country, more investments and attention to the production systems for 'high-value' foods in the crop and livestock sub-sectors are needed. Efforts should not only focus on production by the household or in the locality itself but also on production in commercial clusters, since price rises there make an important contribution to local food price rises overall. Attention to production is important as efforts to achieve improvements in nutritional outcomes in Ethiopia have mostly focused on improving nutrition knowledge (dietary culture) through behavioral change communication. While important and successful (e.g., Kim et al. 2016, Abebe et al. 2016), improving access to and achieving low prices for these nutritious foods also have an important role to play as part of multisectoral efforts to improve nutritional outcomes.

Trade policies play a role in improving affordability, so not only local production situations should be looked at. The effects of exchange rates changes are found in the prices for all food items given indirect effects through the costs of intermediary inputs, such as chemical fertilizers, agro-chemicals and improved feed ingredients. The overvalued exchange rates that have been in vogue in Ethiopia in the last decade have kept food prices low. However, we find that this price effect was more so for cereals than for nutritious foods. A re-alignment of the exchange rate more in line with market forces might reduce the relative prices of nutritious foods improving the access of poor households to them. Moreover, food markets are found not to be uniformly well integrated across the country with more remote markets characterized by higher volatility in prices for nutritious foods. Further efforts to stimulate such integration, such as through investments in road infrastructure, lower transportation costs through encouraging competition, and lower fuel prices, will lead to slightly higher but overall more stable prices. Finally, price controls for those foods, such as fats, oils, and sugar, that are traditionally associated with obesity – which is less of an issue in Ethiopia than in other countries, but is an emerging problem (Gebru et al. 2018) – should best be relaxed so that the prices for these foods reflect their true costs, which likely will raise the prices for these items.

[17] For example, Tafere et al. (2010) used variation in prices in Ethiopia to study to what extent consumption patterns change with changing prices, based on national consumption survey data. They estimated that price elasticities of most food items were close to -1.0 suggesting that a 10 percent increase in prices is associated with a 10 percent decrease in consumption.

[18] As noted in other growing economies, the relative importance of cereals in total food expenditures is already decreasing in Ethiopia. We are beginning to see a shift toward more preferred, but also more expensive foods, including animal-source foods (Worku et al. 2017).

REFERENCES

Abay, K., and K. Hirvonen. 2017. "Does market access mitigate the impact of seasonality on child growth? Panel data evidence from North Ethiopia." *Journal of Development Studies* 53 (9): 1414-1429.

Abebe, Z., G.D. Haki, and K. Baye. 2016. "Health Extension Workers' Knowledge and Knowledge-Sharing Effectiveness of Optimal Infant and Young Child Feeding Are Associated with Mothers' Knowledge and Child Stunting in Rural Ethiopia." *Food and Nutrition Bulletin* 37 (3): 353-363.

Abegaz, G.A., I.W. Hassen, and B. Minten. 2018. *Consumption of animal-source foods in Ethiopia: Patterns, changes, and determinants.* ESSP Working Paper 113. Addis Ababa: International Food Policy Research Institute.

Aggarwal, A., P. Monsivais, and A. Drewnowski. 2012. "Nutrient intakes linked to better health outcomes are associated with higher diet costs in the US." *PLoS ONE* 7 (5): e37533. doi: 10.1371/journal.pone.0037533.

Arimond, M., and M.T. Ruel. 2004. "Dietary diversity is associated with child nutritional status: Evidence from 11 Demographic and Health Surveys." *The Journal of Nutrition* 134 (10): 2579-2585.

Armington, P. 1969. "Theory of Demand for Products Distinguished by Place of Production." *IMF Staff Papers* 16: 159-178

Assefa, T., G. Abebe, I. Lamoot, and B. Minten. 2016. "Urban food retailing and food prices in Africa: The case of Addis Ababa (Ethiopia)." *Journal of Agribusiness in Developing and Emerging Economies* 6 (2): 90-109

Bachewe, F. and A.S. Taffesse. 2017. "Supply response of smallholder households in Ethiopia." In *The Economics of Teff, Ethiopia's Biggest Cash Crop,* edited by B. Minten, A.S. Taffesse, and P. Brown, 183-205. Washington, DC: International Food Policy Research Institute.

Bachewe, F., B. Minten, and F. Yimer. 2017. *The rising costs of animal-source foods in Ethiopia: Evidence and implications*. IFPRI-ESSP Working Paper 108. Addis Ababa: International Food Policy Research Institute.

Bachewe, F., G. Berhane, B. Minten, and A.S. Taffesse. 2018a. "Agricultural transformation in Africa? Assessing the evidence in Ethiopia." *World Development* 105: 286-298.

Bachewe, F.N., B. Minten, F. Tadesse, and A.S. Taffesse. 2018b. *The evolving livestock sector in Ethiopia: Growth by heads, not by productivity*. ESSP Discussion Paper 122. Addis Ababa: International Food Policy Research Institute.

Baffes, J., V. Kshirsagar, and D. Mitchell. 2017. "What drives local food prices? Evidence from the Tanzanian maize market." *The World Bank Economic Review 33* (1): 160-184.

Barrett, C.B. 1997. "Liberalization and food price distributions: ARCH-M evidence from Madagascar." *Food Policy* 22(2): 155-173.

Baum, C. 2004. *xttest2: A Stata module to implement the Breusch-Pagan LM test for cross-sectional correlation in fixed effects model*. (Statistical Software Components S457237). Boston, MA: Boston College Department of Economics.

Baum, C. and V. Wiggins. 1999. *bpagan: A Stata module to calculate the Breusch-Pagan LM statistic to test for ARCH effects.* (Statistical Software Components S457237). Boston, MA: Boston College Department of Economics.

Brinkman, H.J., S. de Pee, I. Sanogo, L. Subran, and M.W. Bloem. 2010. "High food prices and the global financial crisis have reduced access to nutritious food and worsened nutritional status and health." *The Journal of Nutrition* 140 (1): 153S-161S.

CSA (Central Statistical Agency) and ICF International. 2012. *Ethiopia Demographic and Health Survey 2011*. Addis Ababa, Ethiopia and Calverton, MD, USA: CSA and ICF International.

CSA (Central Statistical Agency) and ICF International. 2017. *Ethiopia Demographic and Health Survey 2016 Key Indicators Report*. Addis Ababa, Ethiopia and Calverton, MD, USA: CSA and ICF International.

CSA (Central Statistical Agency). 2017. *Country and Regional Level Consumer Price Indices*. Addis Ababa: Federal Democratic Republic of Ethiopia.

De Hoyos, R.E., and V. Sarafidis. 2006. *xtcsd: A Stata module to test for cross-sectional dependence in panel data models*. (Statistical Software Components S457237). Boston, MA: Boston College Department of Economics.

Deaton, A., and A. Tarozzi. 2000. *Prices and Poverty in India.* Research Program in Development Studies, Princeton University. manuscript.

Development Initiatives. 2018. *2018 Global Nutrition Report: Shining a light to spur action on nutrition*. Bristol, UK: Development Initiatives.

Dillon, B.M., and C.B. Barrett. 2015. Global oil prices and local food prices: Evidence from east Africa. *American Journal of Agricultural Economics 98* (1): 154-171.

FAO (Food and Agriculture Organization of the United Nations) and FHI360. 2016. *Minimum Dietary Diversity for Women: A Guide for Measurement.* Rome: FAO.

FAO (Food and Agriculture Organization of the United Nations). 2018. *World Food Situation: Food Price Index*. Accessed 23 June 2018. http://www.fao.org/worldfoodsituation/foodpricesindex/en/. Rome: FAO.

FMoH/UNICEF/EU (Ethiopian Federal Ministry of Health, UNICEF and European Commission Delegation). 2016. *Situation Analysis of the Nutrition Sector in Ethiopia: 2000-2015*. Addis Ababa: FMoH/UNICEF/EU.

Gebru, M., R. Remans, I. Brouwer, K. Baye, M.B. Melesse, N. Covic, F. Habtamu, A.H. Abay, T. Hailu, K. Hirvonen, T. Kassaye, G. Kennedy, C. Lachat, F. Lemma, J. McDermott, B. Minten, T. Moges, F. Reta, E. Tadesse, T. Taye, U. Truebswasser, and M. Vandenberg. 2018*. Food systems for healthier diets in Ethiopia: Toward a research agenda*. IFPRI discussion paper 1720. Washington DC: International Food Policy Research Institute.

Han, E. and L. M. Powell. 2011. “Effect of food prices on the prevalence of obesity among young adults.” *Public Health* 125 (3): 129-35. doi: 10.1016/j.puhe.2010.11.014.

Headey, D., K. Hirvonen, and J. Hoddinott. 2018. “Animal Sourced Foods and Child Stunting.” *American Journal of Agricultural Economics* 100 (5): 1302-1319.

Headey, D., K. Hirvonen, J. Hoddinott, and D. Stifel. 2019. *Rural food markets and child nutrition, American Economics Association Invited Paper.* Atlanta, Georgia: American Economics Association.

Hirvonen, K. 2016. "Rural-urban differences in children's dietary diversity in Ethiopia: a Poisson decomposition analysis." *Economics Letters* 147: 12-15.

Hirvonen, K. and D. Headey. 2018. “Can governments promote homestead gardening at scale? Evidence from Ethiopia.” *Global Food Security* 19:40-47.

Hirvonen, K., and J. Hoddinott. 2017. "Agricultural production and children’s diets: Evidence from rural Ethiopia." *Agricultural Economics*, 48 (4): 469-480.

Hirvonen, K., J. Hoddinott, B. Minten, and D. Stifel. 2017. "Children’s diets, nutrition knowledge and access to markets." *World Development* 95: 303–315.

Hoddinott, J., D. Headey, and M. Dereje. 2015. “Cows, missing milk markets, and nutrition in rural Ethiopia.” *Journal of Development Studies* 51 (8): 958–75.

Hoddinott, J., H. Alderman, J.R. Behrman, L. Haddad, and S. Horton. 2013. “The economic rationale for investing in stunting reduction.” *Maternal & Child Nutrition* 9 (S2): 69-82.

Iannotti, L.L., M. Robles, H. Pachón, and C. Chiarella. 2012. “Food prices and poverty negatively affect micronutrient intakes in Guatemala.” *The Journal of Nutrition* 142 (8): 1568-1576.

Kim, S.S., R. Rawat, E.M. Mwangi, R. Tesfaye, Y. Abebe, J. Baker, E.A. Frongillo, M. Ruel, and P. Menon. 2016. "Exposure to large-scale social and behavior change communication interventions is associated with improvements in infant and young child feeding practices in Ethiopia." *PLoS ONE* 11 (10): e0164800.

Krueger, A.O., M. Schiff, and A. Valdés. 1988. “Agricultural incentives in developing countries: Measuring the effect of sectoral and economywide policies.” *The World Bank Economic Review 2* (3): 255-271.

Melaku, Y.A., A.M. Temesgen, A. Deribew, G.A. Tessema, K. Deribe, B.W. Sahle, S.F. Abera, T. Bekele, F. Lemma, A.T. Amare, O. Seid, K. Endris, A. Hiruye, A. Worku, R. Adams, A.W. Taylor, T.K. Gill, Z. Shi, A. Afshin, and M.H. Forouzanfar. 2016. "The impact of dietary risk factors on the burden of non-communicable diseases in Ethiopia: findings from the Global Burden of Disease study 2013." *International Journal of Behavioral Nutrition and Physical Activity* 13 (1):122.

Minten, B., D. Stifel, and S. Tamru. 2014. “Structural transformation of cereal markets in Ethiopia.” *Journal of Development Studies 50* (5): 611-629.

Minten, B., E. Tamru, E. Engida, and K. Tadesse. 2016. “Feeding Africa's cities: The case of the supply chain of teff to Addis Ababa.” *Economic Development and Cultural Change* 64 (2): 265-297.

Moller, L.C. 2015. *Ethiopia’s great run: the growth acceleration and how to pace it*. Washington, D.C.: World Bank Group.

Pesaran, M.H. 2004. *General diagnostic tests for cross section dependence in panels* (IZA Discussion Paper No. 1229). Munich: CESIfo.

Popkin, B.M., L.S. Adair, and S.W. Ng. 2012. "Global nutrition transition and the pandemic of obesity in developing countries." *Nutrition Reviews* 70 (1): 3-21.

Powell, L.M., J.F. Chriqui, T. Khan, R. Wada and F.J. Chaloupka. 2013. “Assessing the potential effectiveness of food and beverage taxes and subsidies for improving public health: a systematic review of prices, demand and body weight outcomes.” *Obesity Reviews* 14 (2): 110-28. doi: 10.1111/obr.12002.

Schmidt, E., P.A. Dorosh, M.K. Jemal, and J. Smart. 2018. *Ethiopia's spatial and structural transformation: Public policy and drivers of change*. ESSP discussion paper 119. Addis Ababa: International Food Policy Research Institute.

Shively, G., and G. Thapa. 2016. “Markets, transportation infrastructure, and food prices in Nepal.” *American Journal of Agricultural Economics* 99 (3): 660-682.

Sibhatu, K.T., and M. Qaim. 2017. “Rural food security, subsistence agriculture, and seasonality.” *PloS One* 12 (10): p.e0186406.

Stifel, D., and B. Minten. 2017. "Market Access, Welfare, and Nutrition: Evidence from Ethiopia." *World Development* 90: 229-241.

Swindale, A., and P. Bilinsky. 2006. *Household Dietary Diversity Score (HDDS) for Measurement of Household Food Access: Indicator Guide*. Washington, DC: Food and Nutrition Technical Assistance Project, Academy for Educational Development (FANTA, AED).

Tafere, K., A.S. Taffesse, S. Tamiru, N. Tefera, and Z. Paulos. 2010. *Food demand elasticities in Ethiopia: Estimates using household income consumption expenditure (HICE) survey data*. Ethiopia Strategy Support Program II Working paper 11. Addis Ababa: International Food Policy Research Institute.

UNICEF. 1998. *The State of the World's Children 1998*. New York: Oxford University Press.

Walker, R.E., C.R. Keane, and J.G. Burke. 2010. "Disparities and access to healthy food in the United States: A review of food deserts literature." *Health & place* 16 (5): 876-884.

Warren, A.M., and E.A. Frongillo. 2017. "Mid-level actors and their operating environments for implementing nutrition-sensitive programming in Ethiopia." *Global Food Security*, forthcoming.

WHO (World Health Organization). 2008. *Indicators for assessing infant and young child feeding practices: part 1: definitions*. Conclusions of a consensus meeting held 6-8 November 2007 in Washington DC, USA. Geneva: World Health Organization.

Wiggins, S., S. Keats, E. Han, S. Shimokawa, J. Alberto, V. Hernández, and R.M. Clara. 2015. *The rising cost of a healthy diet.* Changing relative prices of foods in high-income and emerging economies. London: Overseas Development Institute.

Worku, I.H., M. Dereje, B. Minten, and K. Hirvonen. 2017. "Diet transformation in Africa: The case of Ethiopia." *Agricultural economics 48* (S1): 73-86.

World Bank. 2014. *Ethiopia: Poverty Assessment*. Report AUS6744. Poverty Global Practice. Africa Region. Washington, DC: World Bank Group.

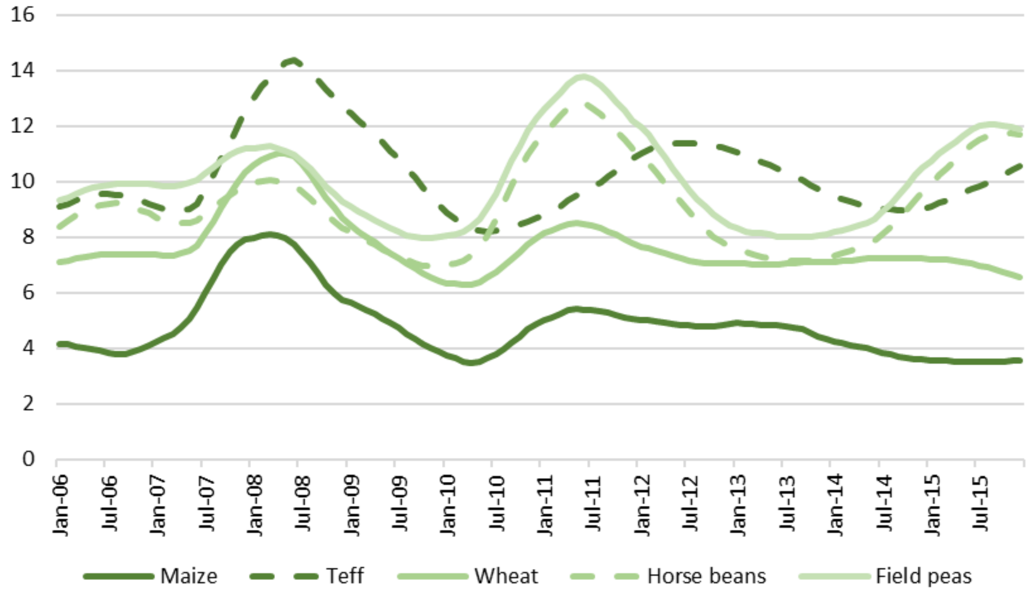
World Bank. 2018. *Commodity Markets: Commodity Price Data (The Pink Sheet).* Accessed 23 June 2018. http://www.worldbank.org/en/research/commodity-markets. Washington, DC: World Bank Group.

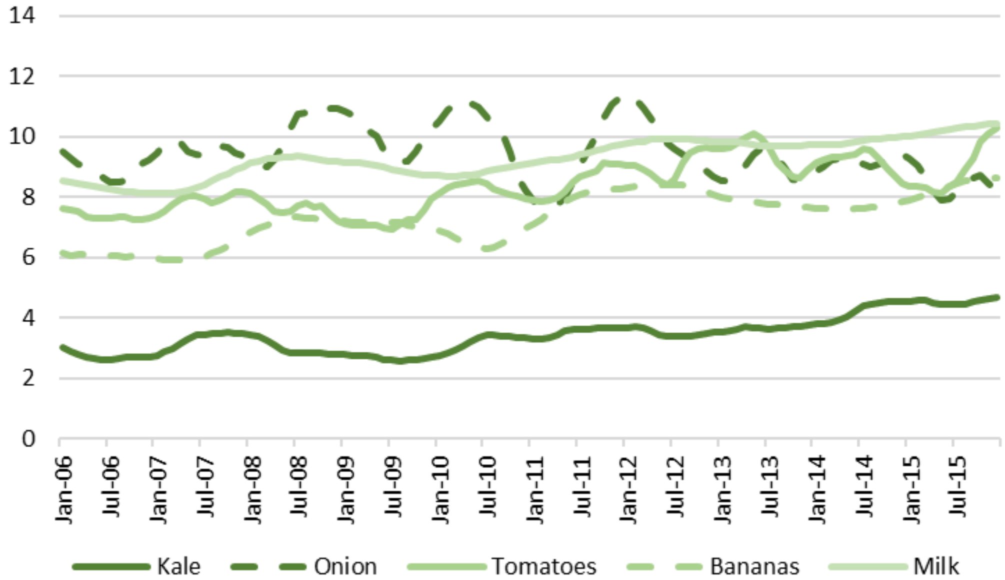
World Bank. 2019. *Ethiopia Economic Update 7. Special topic: Poverty and household welfare in Ethiopia, 2001 - 2016*. Washington, DC: World Bank Group. Downloaded on May 28th, 2019 from: http://documents.worldbank.org/curated/en/432421554200542956/pdf/Special-Topic-Poverty-and-Household-Welfare-in-Ethiopia-2011-2016.pdf.

Xu, X., J.N. Variyam, Z. Zhao, and F.J. Chaloupka. 2014. "Relative food prices and obesity in U.S. metropolitan areas: 1976-2001." *PLoS One* 9 (12): e114707. doi: 10.1371/journal.pone.0114707.

Zerfu, T.A., M. Umeta, and K. Baye. 2016. "Dietary habits, food taboos, and perceptions towards weight gain during pregnancy in Arsi, rural central Ethiopia: a qualitative cross-sectional study." *Journal of Health, Population and Nutrition* 35 (22): 1-7.

ANNEX 1: TRENDS IN REAL RETAIL PRICES OF FOOD ITEMS USED IN THE ECONOMETRIC ANALYSIS





Source: Authors' analyses
Note: Real retail prices are 12-month moving averages.

ANNEX 2: DIAGNOSTIC TESTS OF CHARACTERISTICS OF THE PRICE SERIES USED IN THE ECONOMETRIC ANALYSIS

The dependent variable as well as several of the explanatory variables used in the econometric analyses are price series. We test the stationarity of these variables to avoid misleading results that may occur if the price series are spuriously correlated or appear correlated only because of the common trend in them. We applied the Breitung panel unit-root tests to the price series. Results of these analyses are provided in Annex Table 1. The results indicate that real retail prices, the dependent variable, are stationary at a 1 percent level of significance for all food types except cooking oil. Real retail prices of border markets are stationary for 12 of the 14 food items, while Addis Ababa retail prices are non-stationary for four items. High productivity area retail prices are stationary for 11 of the 12 items for which data are available. Moreover, the real price of fuel is found to be stationary, while the real exchange rate is non-stationary. Given that the dependent variable is stationary and the prices of most items are stationary in most markets, we conduct the analyses using the variables in levels.

Annex Table 1: Results of Breitung panel unit-root tests (estimates of lambda)

Item	Real price, log	High productivity markets price, log	Addis Ababa real price, log	Border market real price, log	Fuel real price (birr/liter), log	Real monthly exchange rate (birr/USD), log
Cereals						
Maize	-13.964	-11.993	-9.777	-11.840	-7.30	14.96[c]
Teff	-7.405	-5.694	-4.781	-6.258		
Wheat	-11.654	-17.083	-4.521	-10.361		
Nutritious foods						
Horse beans	-6.419	-6.710	0.484[c]	0.349[c]		
Field peas	-8.332	-12.168	-5.601	-7.370		
Kale	-21.499	-28.555	-13.209	-19.874		
Bananas	-14.098	-9.970	-5.413	-18.759		
Onion	-23.308	-25.904	-17.862	-18.085		
Tomatoes	-26.227	-32.887	-28.700	-33.352		
Beef	-7.107	-1.372[a]	1.139[c]	-4.676		
Milk	-13.746	-1.015[c]	0.342[c]	-23.548		
Eggs	-16.11	-7.846	-7.675	-3.211		
Cooking oil and sugar						
Cooking oil	1.159[c]	_	10.140	0.517[c]		
Sugar	-5.357	_	-0.138[c]	-2.078[b]		

Source: Authors' analyses
Notes: All estimates significant at 1% level except those with superscripts of a, b, and c, which are significant at 5%, 10%, and not significant, respectively.

As they stand, the models specified in section 2 assume cross-sectional independence of errors. However, food prices in a given zone may be correlated not only with prices in the three (regional, boundary, and Addis Ababa) markets but also with prices in other zones, making the assumption of cross-sectional independence a suspect. We test the validity of the assumption using Pesaran's (2004) CD test and the Breusch-Pagan LM test.[19] Results of these tests are provided in Annex

[19] We use xtcsd, a user written Stata code (De Hoyos and Sarafidis 2006), to implement Pesaran's (2004) CD test and xttest2 (Baum 2004) to implement the Breusch-Pagan LM test.

Table 2 along with results testing for Autoregressive Conditional Heteroskedasticity (ARCH) effects[20] and the absence of first order serial autocorrelation in the data.

Annex Table 2: Results of diagnostic tests

Item	Test of cross-section dependence (CSD) of errors		ARCH effects Lagrange multiplier (LM) test	Wooldridge test for autocorrelation
	Pesaran's CSD statistic	Breusch-Pagan χ2 statistic	Breusch-Pagan LM statistic	F-statistic
Cereals				
Maize	15.40	4415.21	39,263.1	542.25
Teff	13.53	2892.55	23,033.2	609.90
Wheat	13.66	2787.40	23,479.2	940.01
Nutritious foods				
Horse beans	17.27	2510.88	30,810.2	341.11
Field peas	42.84	4947.21	29,532.4	222.55
Kale	5.53	2848.92	28,754.5	289.54
Bananas	3.61	2176.93	14,334.7	370.20
Onion	9.88	2808.19	12,793.1	702.94
Tomatoes	11.50	1094.89	9,882.7	330.20
Beef	26.03	4506.47	83,241.5	515.12
Milk	0.58 [c]	1983.90	47,737.1	281.93
Eggs	19.94	3939.46	30,677.4	488.68
Cooking oil and sugar				
Cooking oil	32.46	6747.92	86,603.0	255.42
Sugar	54.79	9675.40	153,929.8	136.87

Source: Authors' analyses. ARCH = Autoregressive Conditional Heteroskedasticity.
Notes: All estimates significant at 1% level except the one for milk with a superscript of c, which is not significant.

The Lagrange multiplier tests for ARCH effect (column 4) reject the null hypothesis of homoscedasticity in favor of first-order autoregressive conditional heteroskedasticity for all items. Moreover, results of the Wooldridge tests of the null hypothesis of no first-order autocorrelation (last column) reject the null hypothesis for all items in favor of the alternative hypothesis of first-order autocorrelation.[21]

Results of Pesaran's (2004) CD and the Breusch-Pagan LM tests indicate that the null hypothesis of cross-sectional independence of errors is rejected for all items except milk in the Pesaran's CD test. Both tests are implemented by taking the sum of correlation coefficients of residuals of the cross sections. Pesaran's (2004) CD test statistic is computed using the formula: $\sqrt{\left(\frac{2T}{N*(N-1)}\right)} * \sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\bar{\rho}_{ij}$; where T is the number of periods; N is the number of panels/cross-sections; and $\bar{\rho}_{ij}$ is the correlation coefficient of residuals of panels i and j. We find that it is extremely difficult to not reject the null hypothesis of cross-sectional independence using this test.[22]

[20] While conducting the ARCH effects test for six items, we drop some zones missing 45 or more of the 120 monthly observations, as the test could not run without dropping such panel members.

[21] We use the user written Stata codes of bpagan (Baum and Wiggins 1999) and xttest2 (Baum 2004) for the Wooldridge test of first-order autocorrelation and ARCH effects, respectively.

[22] We conduct a simple exercise to check the difficulty of non-rejection using Pesaran's CD test. We first divide the 55 administrative zones in the analysis into two groups (of 28 and 27 zones) by assigning the zone with the lowest zonal code to the first group, the zone with the second lowest code to the second group, so forth. Then we consider residuals obtained from the selected model specifications and stationary international prices of 28 items (World Bank 2018), which we deflate using international food price index (FAO 2018) and cover the same period studied here. Then for each of the 28 zones in the first group, we replace the residuals in odd numbered months by the price of one of the 28 items in the corresponding year and month. For each of the 27 zones in the second group we replace the residuals in even numbered months by the price of the first 27 items. Pesaran's CD test rejects the null hypothesis of cross-sectional independence of the data so constructed for each of the food items in our analyses, including milk.

Given that there are no methods to correct the standard errors for the panel ARCH/GARCH models (Shively and Thapa 2016), we estimate the autoregressive version of the equations corrected with Driscoll-Kraay standard errors as well as using Pesaran and Smith (1995) Mean Group (MG) estimator. The qualitative implications of the estimates obtained from the latter analyses are mostly similar.

Furthermore, we repeat the exercise replacing the residuals over the entire period by the international prices for zones in the first group, while leaving intact residuals of zones in the second group and vice versa. Finally, we repeat the exercise by artificially reversing the months in the international price data. That is, by assigning the first month in the period studied (January 2006) to the data point in the last month, the second month to the data point in the month second from last, and so forth. The test rejects cross-sectional independence at the 1% level of significance in 71 of the cases and at the 5% level in one case.

ANNEX 3: ESTIMATES OF PARAMETERS THAT CHARACTERIZE THE REAL PRICE EQUATIONS

We provide below the log-likelihoods and AIC obtained by estimating the five specifications for the three multi-item price equations. Results of log-likelihood ratio tests indicate that the asymmetric GARCH (AGARCH) model is preferred to all other specifications for the real price equation of nutritious foods, while the threshold GARCH (TGARCH) model performs superior for the joint price equation of cooking oil and sugar. In the cereals real price equation, AGARCH performs slightly better than both GARCH and TARCH, while TARCH is no different from GARCH. However, the variable indicating asymmetric response is insignificant in both AGARCH and TARCH. So, we present results of the GARCH model for cereals.

Annex Table 3: Comparison of log-likelihoods and Akaike Information Criterion of different models considered for the analysis

Equation	Autoregressive model		ARCH model		GARCH model		AGARCH model		TGARCH model	
	Log-Likelihood	AIC	Log-Likelihood	AIC	Log-Likelihood	AIC	Log-Likelihood	AIC	Log-Likelihood	AIC
Cereals	18859	-37631	22200	-44269	22578	-45024	22582	-45030	22579	-45023
Nutritious foods	16942	-33777	32965	-65773	34407	-68654	34457	-68752	34449	-68737
Cooking oil and sugar	15084	-30087	18362	-36610	19379	-38642	19397	-38676	19415	-38712

Source: Authors' analyses. AIC = Akaike Information Criterion; ARCH = Autoregressive Conditional Heteroskedasticity; GARCH = Generalized ARCH; AGARCH = Asymmetric GARCH; TGARCH = Threshold GARCH.

ABOUT THE AUTHORS

Fantu Nisrane Bachewe is a Research Coordinator in IFPRI's Ethiopia Strategy Support Program (ESSP) in the Development Strategy and Governance Division (DSGD) of IFPRI, based in Addis Ababa. **Bart Minten** is Program Leader of ESSP and a Senior Research Fellow in DSGD of IFPRI, based in Addis Ababa.

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE
1201 Eye St, NW | Washington, DC 20005 USA
T. +1-202-862-5600 | F. +1-202-862-5606
Email: ifpri@cgiar.org | www.ifpri.org | www.ifpri.info

IFPRI–ESSP ADDIS ABABA
P.O. Box 5689, Addis Ababa, Ethiopia
T. +251-11-617-2000 | F. +251-11-667-6923
Email: ifpri-essp@cgiar.org | http://essp.ifpri.info

POLICY STUDIES INSTITUTE
P.O. Box 2479, Addis Ababa, Ethiopia
T. +251.11-550-6066; +251-11-553-8633 | F. +251-11-550-5588
http://psi.gov.et/

USAID FROM THE AMERICAN PEOPLE
UKaid from the British people
European Union

The Ethiopia Strategy Support Program (ESSP) is managed by the International Food Policy Research Institute (IFPRI); is jointly implemented with the Policy Studies Institute (PSI); and is financially supported by the United States Agency for International Development (USAID), the Department for International Development (DFID) of the government of the United Kingdom, and the European Union (EU). The research presented here was conducted as part of the CGIAR Research Program on Policies, Institutions, and Markets (PIM), which is led by IFPRI. This study is also partially made possible by the generous support of the American people through USAID under the Feed the Future Innovation Lab for Livestock Systems (LSIL), which is implemented by the Institute of Food and Agricultural Sciences of the University of Florida in partnership with the International Livestock Research Institute (ILRI).This publication has been prepared as an output of ESSP and has not been independently peer reviewed. Any opinions expressed here belong to the author(s) and are not necessarily representative of or endorsed by IFPRI, PSI, USAID, DFID, EU, University of Florida, ILRI, PIM, or CGIAR.