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Analysis of long-term prices of micronutrient-dense and starchy staple foods in developing countries

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Abstract

The continued price increase in food commodities has long been a concern to academia and policymakers because of its substantial impact on poor consumers. Existing literature has concentrated on the cost of micronutrient-dense and starchy staple foods and the price rise in different commodities. Yet, the long-term price growth of micronutrient-dense and starchy staple foods and the price growth gap between micronutrient-dense foods and starchy staple foods have not been given much attention. The paper aimed to estimate the long-term trends in prices and volatility of micronutrient-dense and starchy staples and identify factors that have sustained the growth in prices of food commodities in developing countries. We have used the autoregressive and panel autoregressive distributed lag models to analyse the trends in relative prices and the effects of income growth. The results showed that micronutrient-dense food prices in real terms grew on average by 0.03% per month more than starchy staple food prices, with the expectation of a 12% growth gap in the next 30 years. The volatility of micronutrient-dense food items exceeds starchy staple foods in most domestic markets. Also, the prices of micronutrient-dense foods were more volatile in international markets than in most developing countries. Income growth in developing countries was one of the factors that contributed to the declining relative price of micronutrient-dense food commodities. Other factors, such as the high production of staple foods and their price stabilization policies, may have caused price trends to persist. Policies that enhance price stabilization for micronutrient-dense foods, supplementation, fortification, dietary diversity, and nutrition-sensitive interventions such as biofortification may be adopted in developing countries.

Keywords: Food price, Micronutrient-dense and starchy staple foods, Price trend, Price volatility

Introduction

Prices of food commodities have continued to increase over the years. The world food prices doubled from 59 in January 2000 to 112 in January 2020. For instance, in developing counties like Uganda, prices of major food items such as beans, cassava, and bananas increased by 4%, 18%, and 300% between 2008 and 2020, respectively (FAO 2020). Global food commodity prices are partially transmitted to domestic markets (Minot 2010). The rise in prices affects the welfare of poor consumers in developing countries. Mbegalo and Yu (2016) showed that price spikes resulted in more households slipping into poverty in Tanzania. Another effect of price rise is increased stunting levels among children below five years (Chibuye 2015; Lyu et al. 2015; Headey and Alderman 2019). Poor households respond to price changes by prioritizing the consumption of starchy staple foods over micronutrient-dense diets. The families would reduce buying animal source foods, vegetables, fruits, and pulses and purchase cereals and tubers rich in carbohydrates. Still, Block et al. (2004) study demonstrated that mothers in poor households reduce the frequency and quantity of food eaten in general and feed their children when rice prices increase. The effects of coping behaviour of families when the price changes are seen in the wasting of mothers and reduction in the blood haemoglobin levels in children under five years (Block et al. 2004). French et al. (2019) found that low-income households had a lower healthy eating index than their higher-income counterparts.

An increase in food prices can also be an opportunity than the risk for low-income households producing and consuming micronutrient-dense foods. A divergent growth of prices between micronutrient-dense commodities and starchy staple foods may induce poor farmers to sell more of the micronutrient-dense foods produced and consume less. Magrini et al. (2016) provided evidence that farmers having starchy staple food crops in sub-Saharan Africa respond to price signals by adjusting their acreage, production, and market supply. Ntakyo and van den Berg (2019) showed that Ugandan households that produced rice for the market had lower calorie intake. These examples point to reduced quantities available for consumption when prices increase for starchy staple foods, which might be the case with micronutrient-dense foods.

One of the reasons why low-income households are affected most by price increases is the differential income elasticities of food commodities (Wood et al. 2009; Bouis 1992; Bouis and Haddad 1992; Subramanian and Deaton 1996). Engel had initially postulated this relationship between household income and expenditure on non-food and food commodities. Several studies have expanded Engel's law to analyse the share of household income allocated for micronutrient-dense food and starchy staple food commodities. These studies have concluded that households spend more on starchy staples than on micronutrient-dense foods when prices of food commodities increase (Nsabimana et al. 2020; Dizon et al. 2019; Amfo et al. 2019). Though these studies prove that income affects commodity prices, some caveats exist. First, the effect of income on the costs of commodities in these studies is specific to food commodity, for instance, vegetable, cereals, and roots, which does not provide an aggregate picture of starchy foods. Secondly, the studies consider household characteristics in their analysis. Therefore, in these studies, the effect of income on relative prices of micronutrient-dense food is implied.

Past studies on healthy foods that involve price analysis have concentrated on the availability and affordability of food diets (Barosh et al. 2014; Alemu et al. 2019; Dizon et al. 2019), the price changes of food items from one period to another (Meenakshi 2016). These studies have found that healthy diets are costlier than calorie-rich diets. At the same time, studies on the relative prices of healthy food diets (Rao et al. 2013; Headey and Alderman, 2019; Wiggins et al. 2015; Bachewe et al. 2017) have concluded that nutritious diets are expensive. First, the studies are country-specific (Wiggins et al. 2015; Bachewe et al. 2017) and compared specific food item price increases in meat against rice prices (Meenakshi 2016). Secondly, some studies focus on diets, not food commodities, and are based on cross-sectional data sets where the researchers had not analysed the trends. Lastly, some studies use simple trend analysis, which does not consider the static properties of data. A more extraordinary rise in the price of micronutrient-dense food commodities than starchy staple food commodities may result in nutrition challenges like micronutrient deficiency. We extend the literature on the cost of micronutrient-dense diets by estimating the trends in the growth and volatility in prices of micronutrient-dense and starchy staple food items using time series econometric methods that address static data problems at the national and global levels. We also explore the application of Engle's law with the relative price of micronutrient-dense food items.

In this paper, we answer the question, "do prices of micronutrient-dense food commodities grow faster than starchy staple food items and can income explain the variation in relative prices of micronutrient-dense food items"?. Section two offers the data sources for retail prices for several micronutrient-dense and starchy staple food items in 23 developing countries. In section three, we create the methodology used to analyse time series data to test the hypothesis that the prices for starchy staple food items in developing countries increased less than micronutrient-dense food items over the same reference period. Our analysis finds that micronutrient-dense food prices grew on average across all countries by 0.03% per month, more than starchy staple food prices. In section four, we identify several theoretical reasons why prices for micronutrient-dense foods have increased more than starchy staple food in the past and why it is likely that this trend will persist in the future. The observed differential price trend for micronutrient-dense food has implications for the fight to eradicate hidden hunger and calls for sustainable long-run investments in agri-food value chains to lower the costs for bioavailable micronutrients for human consumption.

Methodology

Data and sources

We used the publicly available data set for micronutrient-dense and starchy staple food commodities to analyse the relative price growth of micronutrient-dense food commodities from three sources. These sources are International Monetary Fund (IMF), Global Information and Early Warning System on Food and Agriculture (FAO-GIEWS), and World Bank (Table 12). Preferably, a long period should be more than ten years where the effect of weather, supply, and demand shocks transmitted from international trade, such as the 2007/08 food crisis, or financial markets, like the 2008 global financial crisis or the 1997 Asian financial crisis, are smoothened.

We modified Headey and Alderman (2019) categorizations of foods in our study into starchy staple foods and micronutrient-dense foods since we are interested in the overall price trends of the two groups. The starchy staples include cereals and tubers dense in calories but generally low in micronutrients and quality proteins, while micronutrient-dense foods consist of vegetal and animal source foods. As a result of the inadequate long-term price data, most vegetal foods rich in vitamins and minerals like vegetables and fruits were not used in the analysis except legumes and nuts (rich in protein). The animal source foods are rich in high-quality protein and bioavailable iron, choline, and vitamin B-12.

The IMF data set contains monthly nominal prices for several grains, animal products, fruits, and vegetables from January 1980 to May 2020[1] (IMF 2020). This data set records international export prices, for example, winter wheat free-on-board prices shipped from the Gulf of Mexico. Different from the IMF data set, the FAO-GIEWS price series are country-specific.[2] It contains monthly nominal prices of micronutrient-dense and starchy staple food commodities for 90 countries. The data also list the corresponding real prices deflated by the consumer price index (FAO 2020). The prices were collected from various major cities/towns at the retail or wholesale level. Our hypothesis focused on the consumer level, so we used retail prices in our analysis. The commodities' prices were recorded as national average or specific market location prices. We used the average national price for a particular crop and month as a default. Otherwise, we computed the average national price as a simple arithmetic average from the market prices for a specific commodity and month. FAO-GIEWS did not provide information on the different markets' sizes; therefore, a weighted price average was not feasible to calculate. The data set has different time lengths; for example, for India, data are available from January 2000 until May 2020, while Uganda's data were available from January 2006 until May 2020.

Of the 90 countries in the FAO-GIEWS database, 47 countries only have prices for starchy staple food commodities. Hence, we could not use these countries' data to test the hypothesis as prices for micronutrient-dense food commodities are missing. We are left with 45 countries, where six countries were dropped because the length of the time series for which prices for all food commodities were observed is less than 10 years which is considered a minimum length of the reference period. These six countries are Cote devoir, Russia, Japan, Iraq, Honduras, Yemen, Egypt, and Argentina. In Angola, the only micronutrient-dense food item for which a price was recorded was milk. Given a low per-capita food consumption of milk of only 11.2 kg per capita in 2011 (FAOSTAT 2020), milk is unlikely to be a significant contributor of micronutrients to the diet of poorer segments of the Angolan population. Therefore, we dropped Angola as well. In 7 countries (Honduras, Somalia, Mexico, Guatemala, Rwanda, Thailand, and Tanzania), we observed the prices of micronutrient-dense food commodities at only wholesale level.

In contrast, prices for starchy staple foods were recorded at both wholesale and retail levels. Given the possibility of market imperfections, price movements in wholesale markets may not correlate well with price movements in the retail market. We excluded these seven countries from the analysis because we focused on retail prices. Lastly, we left four countries (Saudi Arabia, Israel, Panama, and Chili) out of the final set as they are classified as high-income countries.

Hence, a total of 23 countries remained for the analysis. The 2018 population of the 23 countries constitute 24% of the world population. Table 1 shows the starchy staples and micronutrient-dense food commodities for which prices were recorded in 23 countries

[1] One can access IMF data from: http://www.imf.org/external/np/res/commod/index.aspx.

[2] http://www.fao.org/giews/pricetool/.

Table 1 Period for starchy staples and micronutrient-dense food prices by country

Country	Period	Number of months	Food commodities
Azerbaijan	January 2006–April 2020	172	Starchy staples: wheat, maize, potatoes. Micronutrient-dense: beef, milk, mutton
Burundi	January 2006–April 2020	172	Starchy staples: maize, cassava, rice. Micronutrient-dense: beans
Botswana	January 2007–May 2020	161	Starchy staples: maize, sorghum, rice, wheat Micronutrient-dense: beef, milk
Cameroon	January 2005–March 2020	183	Starchy staples: bananas, maize, rice, cassava, wheat, and potatoes. Micronutrient-dense: beans
Costa Rica	January 2000–May 2020	245	Starchy staples: rice, maize, wheat. Micronutrient-dense: beans
Kazakhstan	November 2005–May 2020	175	Starchy staples: potatoes, wheat. Micronutrient-dense: beef, milk
Dominican Republic	January 2006–May 2020	173	Starchy staples: maize, rice. Micronutrient-dense: beans, chicken
El Salvador	January 2006–April 2020	172	Starchy staples: maize, rice, sorghum. Micronutrient-dense: beans
Georgia	January 2004–May 2020	197	Starchy staples: wheat, potatoes. Micronutrient-dense: beef, chicken, pork
Kyrgyzstan	January 2005–May 2020	185	Starchy staples: potatoes, wheat. Micronutrient-dense: beef, mutton
Haiti	January 2005 May 2020	185	Starchy staples: Maize, rice, sorghum. Micronutrient-dense: beans
India	January 2000–May 2020	245	Starchy staples: Rice, potatoes, wheat. Micronutrient-dense: Chickpeas and milk
Mauritania	October 2003–May 2020	200	Starchy staples: wheat, rice. Micronutrient-dense: beef, camel meat
Mongolia	January 2007–May 2020	161	Starchy staples: Potatoes, rice, wheat. Micronutrient-dense: beef, mutton
Nicaragua	September 2007–April 2020	152	Starchy staples: rice, maize. Micronutrient-dense: beans
Peru	January 2000–May 2020	245	Starchy staples: maize, rice, wheat, potatoes Micronutrient-dense: chicken
Samoa	November 2005–April 2020	174	Starchy staples: rice and taro Micronutrient-dense: chicken
Tajikistan	January 2006–April 2020	175	Starchy staples: wheat, potatoes Micronutrient-dense: beef
The Philippines	January 2000–May 2020	245	Starchy staples: rice, maize. Micronutrient-dense: Pork
Tunisia	January 2000–April 2020	244	Starchy staples: wheat, rice, maize, potatoes. Micronutrient-dense: beef, mutton, chicken, milk, chickpeas, fish
Uganda	July 2008–May 2020	143	Starchy staples: matooke, cassava. Micronutrient-dense: beans
South Africa	January 2008–March 2020	172	Starchy staples: wheat, rice, maize,potatoes Micronutrient-dense: beef, chicken, fish
International Prices	January 1980–May 2020	437	Starchy staples: wheat, rice, maize Micronutrient-dense: chicken, pork, fish, beef

during a specific period. The period for which recorded prices may differ by commodity within each country. Table 1 only lists the period for which prices of all items listed for a specific country are recorded in the data set. The time series length varies from 12 years for Uganda to 20 years for Tunisia. Table 1 also lists the international prices recorded by the IMF for wheat, rice, maize, chicken, pork, fish, and beef. These nominal IMF prices for micronutrient-dense and starchy staple food items have the most prolonged reference period of 30 years. We used the consumer price index from the United States Department of Labor to calculate the real international prices.

The last data come from World Bank on the gross domestic product (GDP), purchasing power parity per capita in dollars, real diesel prices per litre in dollars, and average bank lending interest rates (percentage).[3] Data for more extended time series for the mentioned parameters are available than the FAO-GIEWS price series. Still, we used data comparable to the time series period in the FAO-GIEWS.

Empirical specification

To test whether prices of micronutrient-dense food grow faster or are more volatile than starchy staple foods, we used two methods to estimate volatility and price growth. Price growth is the variation in prices from one month to another, also known as the "trend of the price series", while price volatility is the variation overtime period (Manfred et al. 2018; Minot 2014). We first cleaned the data downloaded from FAO-GIEWS, IMF, and World Bank. We filled the missing prices with predicted values from a linear regression of prices against time as it preserves the relationship. Next, we calculated the price index for micronutrient-dense and starchy staple food groups using the Laspeyres index formula (Brown et al. 2012; Kalkuhl et al. 2016). Laspeyres index uses the base prices as the point of reference, and it has greater flexibility in calculating index numbers, and quantities of each food item bought are not required (Diewert 2001). The price index for each of the two food categories was computed as in equation 1.

$$P_t = \frac{\sum_1^n p_{i,t} w_i}{\sum_1^n pb_{i,t} w_i} * 100 \tag{1}$$

where the P_t is the price index of a food group in month t; $p_{i,t}$ is the price of commodity i in month t; n is the number of food commodities for which the price index is computed, and $pb_{i,t}$ is the price at the base month. The base month is the first month of the period, as shown in Table 1. By definition, the price index P_t for $t = 0$ has a value of 100 for the base month, w_i is the weight for a specific commodity i. The price of each food commodity was weighted using the proportion calculated using per-capita food supply. The weighting accounts for a particular food item's contribution to a group's price since food supply drives prices. We obtained the country-specific per-capita energy supply data for a specific food item from the food balance sheet of FAOSTAT for 2017,[4] which is the year for which data were available for all the countries in the analysis.

First, we analysed the long-term prices of food commodities by estimating the price growth for each food group computed as the arithmetic average of the monthly percentage fluctuations in the prices following Wiggins et al. (2015). The monthly percentage changes in the prices for micronutrient-dense and starchy staple food groups were computed using the formula below.

[3] https://data.imf.org/regular.aspx?key=61545867.

[4] Data can be accessed from http://faostat3.fao.org/download/FB/*/E.

$$a = \frac{P_t - P_{t-1}}{P_{t-1}} * 100 \tag{2}$$

where a is the price change between two subsequent periods, P_t is the Laspeyres index for period t, and P_{t-1} is the Laspeyres index for the previous period $t-1$. Another reasonably standard measure for price growth in the economic literature is the difference in the Laspeyres price index between the base period and the month at the end of the time series of a particular food group (Bachewe et al. 2017; Kalkuhl et al. 2016). However, price growth measured using a simple arithmetic average approach may give erroneous results as commodity prices are usually non-stationary and exhibit random walk behaviour.

We determined the trends in the relative prices of micronutrient-dense foods using an autoregressive model, including a trend variable while accounting for a structural break in 2008 and a seasonal effect. This model is specified as below. A dummy variable for the structural break and seasons is included in the model.

$$Y_{it} = \beta_0 + \alpha t + \gamma Y_{i,t-1} + \lambda d_i + \vartheta dt_i + \Phi S_i + \mu_t \tag{3}$$

where α, γ, λ, ϑ Φ are the parameter estimates, Y_{it} is the price index for the food group i (micronutrient-dense food, starchy staple food, and relative food prices) at time t, d_i is the structural break dummy variable, dt_i is the interaction term between the break and time trend, and S_i is the seasonal dummies. The lag length was estimated using the Akaike information criterion. We used one lag since it gave better results than other models with many lags. Baffes and Etienne (2016), Yamada and Yoon (2014), and Erten and Ocampo (2013) have used an autoregressive model in the analysis of long-term price trends of manufactured and primary goods.

Results for the stationary test using augmented Dickey–Fuller (ADF) are presented in Table 8, where, for example, 50% of countries' relative prices exhibit non-stationary series. The first differencing of the non-stationary series was stationary. Then, we tested whether the trend coefficient for micronutrient-dense foods in the international market is more significant than that in domestic markets. The null hypothesis was that the trend coefficient in Eq. 3 is zero for micronutrient-dense food groups, starchy staple food groups, and relative prices of micronutrient-dense foods in each country.

Secondly, in this study, we analysed food price uncertainty, referred to as variation over time. Brown (2012) measured volatility using the "coefficient of variation, which is the ratio of standard deviation and mean of the variable of interest". Minot (2014) noted that the calculated volatility value depends on the data length. In other words, the standard deviation becomes infinity as the length of the data reaches infinity. Using coefficient of variation as a measure of price stability may give false results since it does not address the statistical challenges of time series data (Stock and Watson 2015).

With the challenges in coefficient of variation, we used the standard deviation of returns as the most commonly used in financial markets to measure variability. The "returns" are defined as the "proportional change in commodity prices from one month to the next" (Minot 2014). In practical terms, we computed the return as the change in the logarithm of monthly commodity prices.

$$\text{Unconditional volatility} = \text{stdev}(r)\left[\sum \frac{1}{N-1}(r_t - \bar{r})^2\right]^{0.5} \quad (4)$$

where

$$r_t = \text{In}(P_t) - \text{In}(P_{t-1})$$

$$\bar{r} = \sum \frac{1}{N} r_t.$$

The change in the logarithm of monthly commodity prices makes the commodity prices stationary, and its standard deviation does not depend on the time series length. Any prior information about the size of the period is not necessary, and volatility was based on the available data (Minot 2014). Additionally, we estimated the generalized autoregressive conditional heteroskedasticity (GARCH) model to determine volatility. The GARCH model is a typical technique for modelling volatility in food prices. In the GARCH model, an autoregressive process is specified for the variance, followed by a time series analysis to yield an estimate of the conditional variance of the process at each date in the time series. The GARCH model allows the "variance of returns to change over time as a function of lagged squared residuals and lagged variance" (Gilbert and Morgan 2010; Bachewe et al. 2017). Following Gilbert and Morgan (2010), Bachewe et al. (2017), we specified the model as:

$$h_t = \varphi + \theta_1 h_{t-1} + b_1 \mu_{t-1}^2 \quad (5)$$

where h_t is the conditional variance at month t, μ_{t-1}^2 is the lagged square error term, and φ, θ, b are the parameter estimates. Since it outperforms other models, we estimated the GARCH(1,1) model for micronutrient-dense and starchy staple food groups in all the countries (Hansen and Lunde 2001). Calculating unconditional price volatility for micronutrient-dense and starchy staple foods involves two data sets. We test the null hypothesis that the two sets of prices have the same standard deviation in returns using *vartest.*

Income and the relative price of micronutrient-dense food commodities

Using a panel framework, we estimated the relationship between income and relative prices of micronutrient-dense foods. We used a panel autoregressive distributed lag (ARDL) to model income effects on relative prices of micronutrient-dense food commodities. Pesaran and Shin (1998) have shown that the model produces consistent short-run and long-run parameters with small sample sizes and different variables' integration orders. One of the critical assumptions in the panel ARDL is cross-sectional independence among the variables. The assumption ensures estimates are consistent since cross-sectional correlations are standard features of commodity prices due to the incidence of common shocks and spatial dependence. Another challenge with the relationship between income and prices is reverse causality, which makes the estimates unreliable. Reduced-form equation models are suitable to address such problems. The studies of Pesaran and Smith (1995) have shown that panel ARDL estimates are as reliable as reduced-form models. In fact, in Baffes and Etienne (2016), panel ARDL models could be viewed as reduced-price deterministic models. Following Baffes and Etienne (2016), an error correction version of the panel ARDL model was specified as follows:

$$\Delta N_{it} = \sum_{j=1}^{p-1} \gamma_p^i \Delta N_{i,t-j} + \sum_{j=0}^{q-1} \delta_j^i \Delta X_{i,t-k} + \varphi^i \left[N_{i,t-1} - \left\{ \beta_0^i X_{i,t-1} \right\} \right] + \mu_{it} \tag{6}$$

where N_{it} is the relative prices of micronutrient-dense foods; p and q are the lags of the dependent and independent variables, respectively; X_i are independent variables including income, interest rates, and fuel prices; γ represents the short-term parameters of the lagged dependent variable; δ also refers to the short-run coefficients but of the lagged explanatory variables; φ reflects the speed of adjustment to the long-run equilibrium; β indicates the income in the long run; and μ_{it} is the error term.

We explored the descriptive statistics of relative prices of micronutrient-dense foods, income, fuel prices, and interest rates for the whole data (Table 12). The average relative price of micronutrient-dense food was 1.083, the average gross domestic product (GDP) per-capita purchasing power parity was 8567 dollars, and average interest rates were 15%. We used pooled mean group estimator (PMG) and dynamic fixed estimator (DFE) to estimate the model's coefficients in Eq. 6. Then, we tested the cross section dependence using the Breusch–Pagan test under fixed effects and rejected the null hypothesis of cross-sectional independence.

This study's dependent variable is the relative prices of micronutrient-dense food items. The primary independent variable is income. Most studies found that income increases food prices (Baffes and Etienne 2016; Meenakshi 2016; Gilbert 2010; Hochman et al. 2011). Following Baffes and Etienne (2016), we measured income as the gross domestic product (GDP) per-capita purchasing parity in dollars. The purchasing power parity exchange rate is stable over time, making GDP per-capita purchasing parity applicable for comparing different countries' living standards. Two control variables (interest rates and fuel prices) are included in the panel ARDL as data were not readily available on stock volumes and infrastructural variables. The market lending interest rates measured as percentages in each country have heterogeneous effects on prices. While Byrne et al. (2013); Akram (2009) found negative results, Baffes and Savescu (2014) showed positive effects of interest rates on prices. We measured fuel prices as retail pump prices for diesel per litre. Studies by Zhang et al. (2010) and Bachewe et al. (2017) have demonstrated that commodity prices are affected by fuel prices, while Reboredo (2012) did not find any relationship. Therefore, there is a lack of consensus in the literature about the effect of fuel prices and interest rates on food prices.

Results

Price growth of micronutrient-dense and starchy staple foods in international markets

We begin by examining long-term price trends in micronutrient-dense and starchy staple food items with prices in international markets to provide a background in interpreting trends. Since we are interested in the trend coefficient, we did not present the structural and seasonal dummy results in Eq. 3. The results indicate that prices of micronutrient-dense and starchy staple foods increased between 1980 and 2020. As the prices of starchy staple food increased by 0.13%, the micronutrient-dense food group's prices

Table 2 Trend coefficient for food groups in the international market

Food groups	Coefficient	*P* value
Relative prices of micronutrient-dense foods to starchy staples	0.0014 (0.0007)	0.0112
Starchy staples food commodities	0.0013 (0.0008)	0.0625
Micronutrient-dense food commodities	0.0034 (0.0002)	0.0019
The difference in coefficient between micronutrient-dense foods and starchy staples foods	0.002	0.0314

The figures in brackets are standard errors

Table 3 Trend coefficient for micronutrient-dense food, starchy staples foods, and relative prices

Country	Starchy staples	Micronutrient-dense foods	Relative price	Country	Starchy staples	Micronutrient-dense foods	Relative price
India	0.0009 (0.0010)	−0.0003 (0.0014)	−0.0017 (0.0022)	Peru	−0.00218* (0.0009)	−0.0011* (0.0006)	−0.0125 (0.0215)
Philippians	0.0011** (0.0007)	0.0041** (0.0008)	−0.0003* (0.0001)	Tunisia	0.0008** (0.0003)	0.00356*** (0.0004)	−0.0001 (0.0002)
Azerbaijan	−0.0042 (0.0091)	0.0094 (0.0094)	0.0329 (0.0402)	South Africa	0.0681 (0.0503)	0.00396 (0.0114)	−0.0866* (0.0612)
Costa Rica	−0.0116* (0.00490)	0.00472*** (0.00125)	0.0199 (0.0105)	Samoa	0.0009 (0.0106)	0.0133 (0.0115)	0.0148* (0.0101)
Dominican Republic	−0.00356 (0.00413)	0.0009* (0.0008)	−0.0161* (0.0108)	Tajikistan	0.0058 (0.0134)	−0.0031 (0.0279)	0.0026 (0.0099)
El Salvador	0.00179 (0.0204)	0.0366* (0.0261)	−0.0120 (0.0101)	Kenya	−0.0467* (0.0401)	0.0133* (0.0101)	−0.0450** (0.0215)
Georgia	−0.0009** (0.0006)	0.00295* (0.00215)	−0.00373* (0.00308)	Uganda	−0.0058 (0.161)	0.00712 (0.0995)	−0.0016 (0.105)
Haiti	0.00670* (0.00261)	0.00417 (0.0023)	−0.00708** (0.0043)	Nicaragua	−0.161* (0.0889)	−0.152* (0.0986)	−0.0134 (0.0111)
Kazakhstan	−0.0097 (0.0129)	0.0074 (0.0122)	0.0151* (0.0064)	Burundi	0.00711* (0.00494)	0.00492** (0.0105)	−0.0100** (0.0030)
Mauritania	−0.0024* (0.0019)	−0.0044* (0.0030)	−0.0004 (0.0015)	Botswana	0.00471* (0.0035)	0.0051** (0.0017)	−0.0108* (0.0066)
Mongolia	−0.0485 (0.0572)	−0.0558 (0.0525)	−0.0031 (0.0183)	Cameroon	0.0043 (0.0056)	0.0067 (0.0052)	−0.0014 (0.0016)
Kyrgyzstan	−0.0093 (0.0057)	−0.0156 (0.0157)	−0.0103 (0.0065)				

The figures in brackets are standard errors

increased by 0.34% per month during the same period (Table 2). The F-statistic indicates that prices of micronutrient-dense food groups grew more than starchy staple foods at a 5% significance level. The results from relative prices of micronutrient-dense foods to starchy staples collaborate with these results. We find similar evidence of faster growth of micronutrient-dense food items over starchy staple food items (Table 9) using a simple average of monthly price changes. Manfred et al. (2018) found that the long-term increase in micronutrient-dense foods' price over starchy staple foods was 0.1, slightly lower than what we saw in this paper.

Distribution of food price trends in developing countries

The autoregressive model in equation four was estimated for relative prices, starchy staples food group, and micronutrient-dense food group. The results for the autoregressive model are presented in Table 3. We describe the results in column four as they directly test the hypothesis that micronutrient-dense food grows faster than starchy staple foods. Generally, most countries show a negative trend in the relative prices of micronutrient-dense food items, suggesting that their prices increase more than starchy staples. The negative price trend in eight countries was significant at five or ten percent. In these countries, we found the relative prices of micronutrient-dense foods to decline between 0.01% (Tunisia) and 8% (South Africa) per month.

We found the price of starchy staple food items grows faster in Azerbaijan, Costa Rica, Kazakhstan, Samoa, and Tajikistan. Most of the countries where prices of starchy staples rose more quickly than micronutrient-dense foods are in central Asia. We examined the number of food commodities in the analysis. We found some countries had one food commodity in the micronutrient-dense food group, for example, beans in Burundi, compared to Azerbaijan, with more than one food commodity. It may be that countries with positive relative prices had one micronutrient-dense food in the group. Similar negative results of relative prices are found in some studies that provide evidence for the Prebisch–Singer hypothesis (Yamada and Yoon 2014; Arezki et al. 2014). We obtained similar results when we used average monthly real price percentage change (Table 6) and price change from the base month to the last period in the time series (Table 7)). In both methods, the price of micronutrient-dense food items grows faster than starchy staple food items in over 60% of the countries.

We calculated the overall increase in monthly prices of micronutrient-dense foods over starchy staple foods across developing countries using average monthly real price percentage change. We weighted the average monthly growth in prices by the 2018 population of each country. Therefore, the average price of micronutrient-dense food items increased faster than starchy staple foods by 0.03 percentage points (Table 9). When the overall price gap in commodity prices was compounded in 30 years, it translated to 12%. With poor households consuming more starchy staples, a declining relative price of micronutrient-dense commodities would reduce their consumption of these foods and increase micronutrient deficiency.

Micronutrient-dense food price growth in developing country markets and international markets

We test the hypothesis that prices in developing markets grow faster than in international markets for micronutrient-dense foods. First, we conducted an *F* test for the trend coefficient from Eq. 3 to compare the growth in micronutrient-dense food groups between developing country markets and international markets. In slightly over half of the developing countries' markets, micronutrient-dense food prices grow faster than global micronutrient-dense commodity prices (Fig. 1).

Volatility of micronutrient-dense and starchy staple foods in international markets

We compared the price fluctuation around a long-term trend for micronutrient-dense food items and starchy staple food items first in the international markets and then in domestic markets. The results show the volatility of micronutrient-dense foods was 0.003 percentage points more per month than the volatility of starchy staple foods (Table 4). Results from the GARCH model show a similar pattern (Table 10).

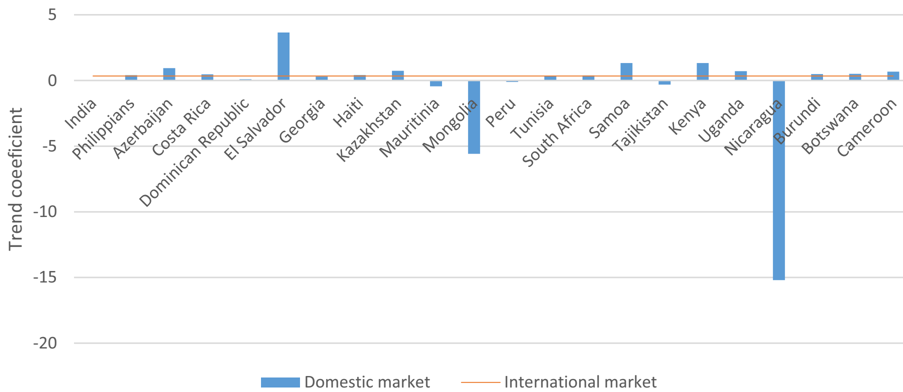

Fig. 1 Trend coefficient for micronutrient-dense food prices in developing and international markets. The *F* statistics indicated that the difference in the coefficient of micronutrient-dense and starchy staples was significant for all the domestic countries and global markets.

Table 4 Unconditional food price volatility in the international market

Food category	Value
Micronutrient-dense food commodities	0.031
Starchy staple food commodities	0.028
P value	0.096

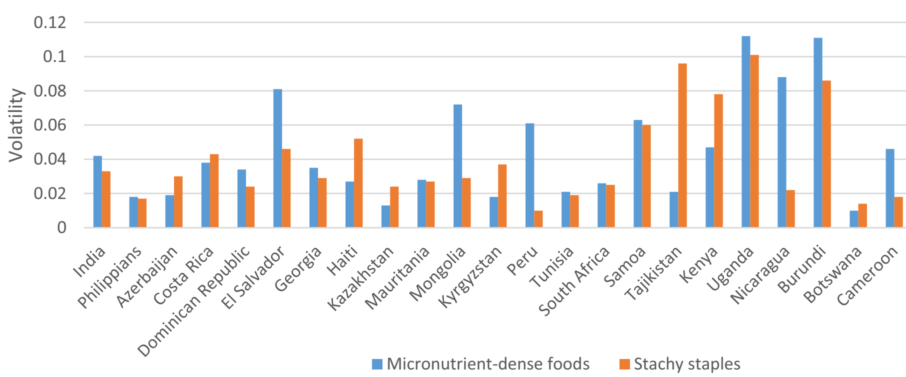

Fig. 2 Unconditional volatility in food prices in developing countries by food group. The F statistics indicated that the difference in the volatility of micronutrient-dense and starchy staples was significant in Dominican Republic, El Salvador, Mongolia, Mongolia, Nicaragua, and Cameroon.

Distribution of food price volatility in developing country markets

Figure 2 presents the standard deviation of returns for micronutrient-dense and starchy staple foods in developing countries. Uganda had the highest volatility of micronutrient-dense and starchy staple foods, while Botswana had the lowest micronutrient-dense foods at 0.01. Our interest was to test whether the prices of micronutrient-dense foods are more volatile than starchy staple foods and therefore did not test for the difference in volatility of the food groups across countries. We used the *vartest* in STATA to determine whether the variation in micronutrient-dense food was more than in starchy staple foods. Generally, in most countries, the variation in prices of micronutrient-dense

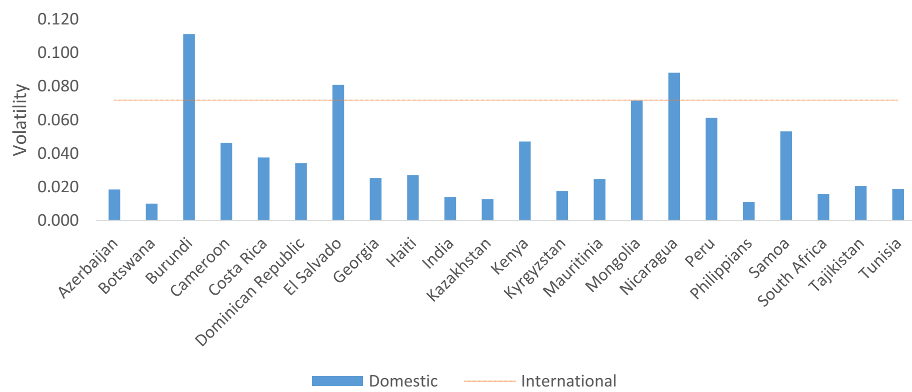

Fig. 3 Unconditional volatility in micronutrient-dense food prices in developing countries and international markets. The F statistics indicated that the volatility of micronutrient-dense foods in all domestic markets was significantly lower than in the global market except in Uganda and Burundi, where it was higher

foods was greater than for starchy staple foods (Fig. 2). The gap in the variation of prices between micronutrient-dense foods and starchy staples was significant in Dominican Republic, El Salvador, Mongolia, Mongolia, Nicaragua, and Cameroon. The analysis of volatility using GARCH showed similar results (Table 10). Most countries with a significant volatility gap between micronutrient-dense and starchy staple food are in Latin America, except Cameroon and Mongolia. The heterogeneous nature of volatility is no surprise as Minot (2014) showed that the volatility of maize increased between 2003 and 2010, while it reduced for beans, millet, and rice in some African countries.

Micronutrient-dense food price volatility in developing country markets and international markets.

We compared the volatility in micronutrient-dense food items in developing countries with volatility for the same group in the international market. Of the 23 countries we analysed, only two countries (Uganda and Burundi) had significantly higher micronutrient-dense food price variances than global prices. In the rest of the countries, the variance of micronutrient-dense foods was lower or equal to that of micronutrient-dense foods in international markets (Fig. 3). One of the reasons micronutrient-dense food prices in global markets may fluctuate more than in national markets is that only a tiny share of world production of micronutrient-dense foods is internationally traded. Using the coefficient of variation, Manfred et al. (2018) found that the variation in non-staple food commodities was higher in the international markets than in domestic markets. Minot (2014) showed mixed results where 62% of rice price series analysed were more volatile in African markets than global markets though rice is tradable like wheat and cooking oil with stable global prices.

The role of income growth in relative prices of micronutrient-dense food commodities

As expected, we found a negative relationship between income and relative prices of micronutrient-dense food items (Table 5). A one percentage increase in GDP per-capita purchasing power parity leads to a 19% decrease in relative prices per year. The results confirm studies by Byrne et al. (2013) and Baffes and Etienne (2016); and Engel's law,

Table 5 PMG and DFE estimates from panel ARDL model for GDP per capita and relative price

Variables	PMG ($p=1, q=1$)	DFE ($p=1, q=1$)
Long-run coefficients		
ln_gdp	−0.190*** (0.050)	−0.076** (0.028)
ln_interest_rates	−0.166*** (0.062)	−0.007* (0.005)
ln_fuel	−0.022 (0.034)	−0.088 (0.064)
ECT	−0.082*** (0.014)	−0.057*** (0.005)
Short-run coefficients		
Δ(ln_gdp)	0.290 (0.469)	0.014 (0.039)
Δ(ln_interest_rates)	0.065 (0.044)	0.005 (0.012)
Δ(ln_fuel)	−0.066* (0.037)	−0.003* (0.002)
_cons	0.183*** (0.034)	−0.018 (−0.44)
Number of observations	4542	4542
Number of countries	23	23
Log-Likelihood	8942	

The figures in the brackets are the standard errors, and *, **, *** are 10%, 5%, and 1% significance levels; p and q are the numbers of lags for dependent and independent variables. ECT is the error correction term

whereas income increases, the share of income allocated for micronutrient-dense foods commodities increases. The differences in income elasticities between micronutrient-dense foods and starchy staple food items have been advanced to explain these relative price changes (Manfred et al. 2018). Studies have demonstrated that the income elasticities of micronutrient-dense food commodities are more outstanding than starchy staple food items (Colen et al. 2018; Boysen 2016). The results also showed a significant negative relationship between interest rates and relative prices. The magnitude of the effect ranges between 0.7 and 16%, depending on the estimation method. This result is consistent with Byrne et al. (2013) and Anzuini et al. (2013), who illustrated that monetary policy was aimed at stabilizing prices. Contrary to the finding, Baffes and Etienne (2016) showed a positive effect of interest rate on the terms of trade.

In the short run, income does not seem to significantly influence the relative prices of micronutrient-dense commodities because of the stickiness of supply. Contrarily, Baffes and Etienne (2016) found a positive and significant short-run effect of income on terms of trade. On the other hand, a one percent increase in fuel prices leads to increased relative prices of micronutrient-dense food commodities by between 0.3% and 6% per year. Most of these studies established that when fuel prices rise, the prices of commodities increase (Bachewe et al. 2017; Saghaian 2010; Gilbert 2010) as the rise in fuel prices may be transmitted to commodities prices (Gilbert 1989; Baffes 2007).

Discussion and implications for policy

We aimed to estimate the trends in micronutrient-dense food items and starchy staple food prices in developing countries and explore whether income can explain the relative prices of micronutrient-dense foods. The analysis shows that the prices for micronutrient-dense foods increased more than for starchy staple foods. Specifically, on average, the prices of micronutrient-dense foods increased by 0.03 percentage points per month more than the prices for starchy staple food items in domestic markets. In other words, micronutrient-dense foods would become 12% more expensive in 30 years than starchy staples. We found exceptions in Azerbaijan, Costa Rica, Kazakhstan, Samoa, and Tajikistan, where the prices of starchy foods increased more than micronutrient-dense foods. Meenakshi (2016), using nationally representative data from India, found prices for non-staples (per unit calorie) relative to cereals grew faster in India. Manfred et al. (2018) found that the prices of non-staples food items increased faster than staple food commodities.

The most plausible explanation for the faster rise in micronutrient-dense than starchy foods is income growth. Results from the panel ARDL model corroborates this, where per-capita income negatively affects the relative prices of micronutrient-dense foods. The income elasticity of demand for micronutrient-dense food items is higher than for starchy staple food items. Colen et al. (2018) have demonstrated that the income elasticity of animal source foods is twice more than that for cereals. With rising GDP, the demand for micronutrient-dense food grows faster, pushing their prices up. In the Philippians, Dominican Republic, Georgia, Kenya, and Botswana, the GDP grew by over 4% per year between 2000 and 2020 (World Bank 2020). Despite income growth in developing countries over the years, its distribution is unequal, not benefiting the poor. In addition, countries with slow GDP growth rates per year (less than 2%), like Haiti and Burundi, have faced disasters and political instability that affect the supply of micronutrient-dense and starchy staples.

Generally, supply factors like the high productivity of starchy staple foods, higher cost of production of micronutrient-dense food items, and more labour intensity of micronutrient-dense food items (Gilbert and Morgan 2010) also explain the price gap. First, many private and public investments have focused on high-yielding starchy staple crops (maize, rice, wheat). For example, over time, these high-yielding innovations have reduced production costs and increased total factor productivity for starchy staple food production, increasing market supply and thereby dampening the long-run effect on staple food prices. Second, micronutrient-dense foods require more natural resources per unit of quantity produced. As these resources get scarcer, the production costs for micronutrient-dense food rise faster than those for starchy staple foods. The production of 1 kg of beef requires five times more water than the production of 1 kg of rice.[5] Third, micronutrient-dense foods require a lot of labour (with few exceptions, such as capital-intensive agro-industrial production for poultry, beef, dairy, and pork) relative to starchy staples. As the costs of labour rise, the costs of production, processing, and preparation of micronutrient-dense food also rise. Furthermore, the higher labour intensity of micronutrient-dense food than staple food is observed in primary production and the entire value chain from farm to fork in wholesale, retail, and domestic household food preparation. Over time, these underlying trends in diverging unit production costs dampen increases in market supply for micronutrient-dense foods compared with the supply of starchy staple foods.

The results also demonstrate that the prices of micronutrient-dense foods are more volatile than starchy staple food items in the Dominican Republic, El Salvador, Mongolia, Mongolia, Nicaragua, and Cameroon. The following reasons explain the volatility gap between micronutrient-dense and starchy staple foods. First, unlike starchy staple

[5] https://www.theguardian.com/news/datablog/2013/jan/10/how-much-water-food-production-waste#:~:text=Meat%20production%20requires%20a%20much,and%204%2C000%20litres%20of%20water.

Table 6 Average monthly price percentage change by food group

Country	Starchy staples	Micronutrient-dense	Difference	Population-weighted average	Country	Starchy staples	Micronutrient-dense	Difference	Population-weighted average
Azerbaijan	0.264	0.090	−0.173	−0.0010	Kenya	0.123	0.269	0.146	0.0042
Botswana	−0.058	0.080	0.138*	0.0002	Kyrgyzstan	0.071	0.129	0.058***	0.0002
Burundi	0.619	1.155	0.536	0.0033	Mauritania	0.004	0.050	0.046	0.0001
Cameroon	0.075	0.291	0.216	0.0030	Mongolia	0.180	0.419	0.239	0.0004
Costa Rica	0.351	0.072	−0.279	−0.0008	Nicaragua	0.110	0.374	0.264	0.0010
Dominican Republic	−0.082	0.075	0.157	0.0009	Peru	0.025	0.014	−0.011	−0.0002
El Salvador	0.301	0.364	0.064	0.0002	Philippians	0.037	0.016	−0.021	−0.0013
Georgia	0.079	0.112	0.033	0.0001	Samoa	0.136	−0.147	−0.283	0.0000
Haiti	0.139	0.188	0.048	0.0003	South Africa	0.110	0.072	−0.038	−0.0012
India	0.018	0.027	0.045	0.0340	Tajikistan	0.914	0.519	−0.395**	−0.0020
Kazakhstan	0.132	0.228	0.095	0.0010	Tunisia	−0.166	0.186	0.352**	0.0023
International	0.277	0.287	0.009		Uganda	1.015	0.580	−0.435	−0.0104

The difference is between micronutrient-dense food and starchy staple food. We tested the significance of the difference in average monthly growth using the Wilcoxon–Mann–Whitney nonparametric as the price increases are not normally distributed. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

foods, micronutrient-dense foods exhibit higher degrees of perishability and face higher post-harvest losses (Headey and Alderman 2019). They also require a much higher degree of market coordination in the value chain for connecting primary producers to final consumers (Sarris 2009; Tadasse et al. 2016; Gilbert and Morgan 2010). Therefore, any disruption in the value chain will likely cause more pronounced price fluctuations in micronutrient-dense foods. Due to perishability and high transportation costs, the price transmission for micronutrient-dense food items is much lower than for starchy staples. These factors, in turn, ceteris paribus, cause a higher price variation among micronutrient-dense food items than starchy staple foods. Third, climate change and related weather shocks, especially in the developing world, may also be another underlying causal determinant for the higher price variation (Gaetano et al. 2018).

A comparison of the micronutrient-dense food volatility in domestic and global markets showed that prices are more volatile in international markets than in domestic markets in most countries. Global markets are less integrated for micronutrient-dense foods than starchy staples, therefore low international price transmission. Much as micronutrient-dense foods are traded (for example, frozen meat or mutton or high-value vegetables and fruits), the traded share is relatively low compared with global production. Sudden changes in demand and supply in extensive exporting or importing countries due to various factors (climatic shocks, macroeconomic, financial crises, export restrictions) make international food prices volatile. In addition, speculation in global food markets through financial markets has been identified as a potential cause of price fluctuation in international food markets. However, recent studies rejected the hypothesis that speculative behaviour increases food prices (Bredin et al. 2021). In countries like Uganda and Burundi, where the production of beans entirely depends on the weather, the price volatility may be greater than in international markets (Tables 6, 7, 8, 9, 10, 11, 12).

Table 7 Change in prices from base month to the last period in the time series by food group

Country	Starchy staples	Micronutrient-dense	Difference	Country	Starchy staples	Micronutrient-dense	Difference
Azerbaijan	31.091	11.810	− 19.281	Kazakhstan	16.642	31.742	15.100
Botswana	− 11.469	11.234	22.703	Kenya	16.356	25.240	8.884
Burundi	32.228	57.529	25.302	Kyrgyzstan	− 0.065	18.892	18.957
Cameroon	10.238	28.278	18.040	Mauritania	− 6.439	4.030	10.469
Costa Rica	45.711	0.378	− 45.333	Mongolia	19.802	22.972	3.170
Dominican Republic	− 21.069	3.033	24.102	Nicaragua	12.158	− 3.321	− 15.479
El Salvador	28.054	5.385	− 22.669	Peru	4.704	− 52.116	− 56.820
Georgia	7.022	14.434	7.411	Philippians	4.305	2.331	− 1.973
Haiti	0.197	24.316	24,119	Samoa	− 8.199	− 64.804	− 56.606
India	3.538	4.006	0.468	South Africa	10.887	8.285	− 2.602
Uganda	51.451	− 4.357	− 55.808	Tajikistan	51.204	57.188	5.983
International	2.198	11.199	9.001	Tunisia	− 56.389	33.507	89.896

The difference is between micronutrient-dense food and starchy staple food

Table 8 Augmented Dickey–Fuller unit root test for the relative price, micronutrient-dense food prices, and starchy staple food prices

Country	Micronutrient-dense foods	Starchy staples	Relative prices	Country	Micronutrient-dense foods	Starchy staples	Relative prices
India	− 2.926	− 5.600***	− 4.819***	Peru	− 4.695***	− 3.401*	− 5.452***
Philippians	− 3.272*	− 4.345***	− 3.562**	Tunisia	− 4.236**	− 2.276	− 2,232
Azerbaijan	− 2.276	− 3.075	− 3.081	South Africa	− 3.947**	− 2.237	− 2.555
Costa Rica	− 1.766	− 1.030	− 2.689	Samoa	− 3.041	− 3.426**	− 3.632**
Dominican Republic	− 4.749	− 2.174	− 3.389*	Tajikistan	− 2.164	− 4.031**	− 3.930**
El Salvador	− 3.280*	− 3.231*	− 4.128**	Kenya	− 1.350	− 1.850	− 1.182
Georgia	− 3.371*	− 2.306	− 2.858	Uganda	− 5.576***	− 4.561**	− 5.117***
Haiti	− 3.825**	− 3.100	− 3.358*	Nicaragua	− 3.339*	− 3.408**	− 3.652**
Kazakhstan	− 1.557	− 2.317	− 1.776	Burundi	− 3.672**	− 2.643	− 3.672**
Mauritania	− 2.025	− 4.298***	− 3.129*	Botswana	− 4.665***	− 3.994**	− 2.289
Mongolia	− 4.496**	− 2.965	− 3.734**	Cameroon	− 3.308*	− 3.095	− 2.815
Kyrgyzstan	− 2.197	− 3.021	− 3.439*	International	− 6.786***	− 4,118**	− 4.482***

Dickey–Fuller test. *, **, *** are 10%, 5%, and 1% significance levels

Policy implications and further research

Concerning policy, the above underlying hypothesized causal factors may make it plausible that prices for micronutrient-dense foods will continue to rise faster than for starchy staple foods in the near and distant future. Global and national food policy

Table 9 Population-weighted relative price of micronutrient-dense food items by category of country

Market	Relative average monthly price growth	Relative unconditional volatility
All developing countries ($n=23$)	0.032**	0.013*
International market	0.009*	0.015

Relative values are calculated by subtracting the, for example, average monthly growth in micronutrient-dense and starchy staple foods and then weighted by the population for developing country markets. *, **, *** are 10%, 5%, and 1% significance levels

Table 10 Conditional volatility in food prices in developing countries by food group

Country	Micronutrient-dense foods	Starchy staples	P-value	Country	Micronutrient-dense foods	Starchy staples	*P* value
India	0.044	0.032	1.000	Peru	0.076	0.010	0.000
Philippians	0.019	0.018	1.000	Tunisia	0.020	0.019	0.469
Azerbaijan	0.019	0.029	1.000	South Africa	0.026	0.022	0.994
Costa Rica	0.035	0.041	0.680	Samoa	0.073	0.060	0.881
Dominican Republic	0.034	0.022	0.004	Tajikistan	0.021	0.097	1.000
El Salvador	0.075	0.047	0.001	Kenya	0.041	0.078	0.944
Georgia	0.029	0.027	0.832	Uganda	0.111	0.099	0.251
Haiti	0.026	0.051	1.000	Nicaragua	0.082	0.022	0.000
Kazakhstan	0.013	0.023	1.000	Burundi	0.110	0.085	0.117
Mauritania	0.029	0.026	0.637	Botswana	0.010	0.015	0.874
Mongolia	0.070	0.028	0.000	Cameroon	0.046	0.018	0.000
Kyrgyzstan	0.017	0.038	1.000				

The parameters presented are "garch" parameters, also known as b1 parameters in Eq. 3, which was our interest. We then tested the difference in the variance using *F* statistics

Table 11 Descriptive for the variables used in the panel autoregressive distributed lag

Variable	Upper-middle-income countries ($n=1728$)	Lower-middle-income countries ($n=1713$)	Low-income countries ($n=1151$)	All developing countries ($n=4592$)	*P* value
Average relative prices	1.123 (0.306)	1.058 (0.400)	1.062 (0.295)	1.083 (0.343)	0.000
Average GDP per-capita PPP (dollars)	13,584 (7398)	6339 (3177)	4350 (4592)	8567 (6739)	0.000
Average interest rates	15.428 (5.198)	13.871 (5.936)	18.181 (7.964)	15.537 (6.480)	0.000

The figures in the brackets are standard deviations

Table 12 Description of the data sources used in the study

Variable	Description	Source
Prices	Monthly nominal prices for several grains, animal products, fruits, and vegetables	IMF
Prices	Monthly nominal and real prices of micronutrient-dense and starchy staple food commodities	FAO-GIEWS
Income	Gross domestic product (GDP), purchasing power parity per capita in dollars	World Bank
Diesel prices	Real diesel prices per litre in dollars	World Bank
Interest rates	Average bank lending interest rates (percentage)	World Bank

could potentially address the potential effect of a faster rise in prices by enhanced research and investment in agriculture nutrition-sensitive interventions like biofortification, high-yielding fruits, vegetables, and livestock (Bouis and Saltzman 2017; Kabunga et al. 2014; Hetherington et al. 2017); supplementation (Tam et al. 2020); and trade and or tax policies (Dizon et al. 2019; World Health Organization 2015).

The few numbers of commodities with price data and the length of available data were a challenge for the study. Ideally, the period covered for the investigation should be the same for all countries, and the choice of food items should include all the main starchy staples and micronutrient-dense food consumed in a country. Despite the data limitations, this study still serves as a good starting point to analyse the difference in price trends between starchy staples and micronutrient-dense foods. It is essential to conduct further analysis on this topic, both on the movement and patterns with a larger sample, and understand some of the underlying causal factors driving the observed differential price trend and price variation. An analysis with unit values from household consumption and expenditure surveys could solve limited data instead of price data from domestic markets.

Abbreviations

GDP	Gross domestic product
ARDL	Autoregressive distributed lag
PMG	Pooled mean group
DFE	Dynamic fixed estimator
GARCH	Generalized autoregressive conditional heteroskedasticity
IMF	International Monetary Fund
FAO-GIEWS	Global Information and Early Warning System on Food and Agriculture

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Author contributions
MZ and AL conceptualized the study, AL collected and analysed the data, and LYK analysed and suggested one of the methodologies. All authors discussed the results and participated in writing of the report. All authors read and approved the final manuscript.

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Availability of data and materials
The cleaned data sets used for the analysis for the study are available from the corresponding author on reasonable request though the data can be accessed from IMF, World Bank, and FAO-GIEWS.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare that they have no competing interests.

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