Seasonality in Local Food Markets and Consumption

Evidence from Tanzania

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Abstract

This paper revisits the extent of seasonality in African livelihoods. It uses 19 years of monthly food prices from 20 markets and three years of nationally representative household panel surveys from Tanzania. Trigonometric specifications are introduced to measure the seasonal gap. When samples are short and seasonality is poorly defined, they produce less upward bias than the common dummy variable approach. On average, the seasonal gap for maize prices is estimated to be 27 percent; it is 15 percent for rice. In both cases it is two and a half to three times higher than in the international reference market. Food price seasonality is not a major contributor to food price volatility, but it does translate into seasonal variation in caloric intake of about 10 percent among poor urban households and rural net food sellers. Rural net food-buying households appear able to smooth their consumption. The disappearance of seasonality from Africa’s development debate seems premature.

This paper is a product of the “Agriculture in Africa—Telling Facts from Myths” project managed by the Office of the Chief Economist, Africa Region and the Jobs Group of the World Bank, in collaboration with the Poverty and Inequality Unit, Development Economics Department of the World Bank, the African Development Bank, the Alliance for a Green Revolution in Africa, Cornell University, Food and Agriculture Organization, Maastricht School of Management, Trento University, University of Pretoria, and the University of Rome Tor Vergata. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The authors of the paper may be contacted at lchristiaensen@worldbank.org.
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**JEL:** D12, D14, D40, D91, I31

**Keywords:** maize, rice, seasonality, Sub-Saharan Africa, calorie, food consumption

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1 Introduction

Seasonality has disappeared from Africa’s development debate.\(^2\) In food prices, the focus has been on volatility (Galtier and Vindel, 2012; World Bank, 2012; Minot, 2014), ignoring the predictable (seasonal) component. Information on seasonal fluctuations in household consumption is even harder to come by. Nonetheless, the welfare consequences of food price seasonality can be substantial, in particular for food security and nutrition (Sahn, 1989; Dercon and Krishnan 2000; Khandker, 2012). Policy responses likely also differ from those appropriate to surprise food price spikes. This paper revisits the extent of seasonality in African livelihoods. It develops a more robust methodology for measuring and comparing the extent of seasonal price variation and explores the extent to which seasonality in food prices transmits into caloric consumption.

A certain degree of seasonality in food prices is unavoidable, even when markets are efficient. Production is cyclical for most staples (especially cereals), necessitating intertemporal arbitrage. Storage costs ensue, driven by the physical cost of storage, the opportunity cost of capital, and post-harvest loss (Affognon, 2015). This drives a wedge between prices before and after the harvest. This price gap can be compounded by high transaction costs across surplus and deficit markets following poor infrastructure, fuel costs (Dillon and Barrett, 2013), transport monopolies (Teravaninthorn and Raballand, 2009), market power along the marketing chain and in storage (even if only seasonal) (Osborne, 2004, 2005), and credit and liquidity constraints for traders. Sell-low, buy-back-high behavior among liquidity constrained households facing imperfect capital markets (Stephens and Barrett, 2011) may further push up the seasonal price

\(^2\) Seasonality in food prices and food consumption was an important subject of study in the 1990s. Since then, the topic has largely disappeared from the policy debate and in project design as well as in the academic literature. The general perception of improved integration of local food markets may have partly motivated the neglect. Nevertheless, substantial seasonality in price movements is still possible even when domestic food markets are better integrated. This can happen, for example, if the timing of production is highly correlated across markets and commodities, and if domestic food markets are poorly integrated with world markets (and/or those across neighboring countries). Furthermore, as Zant (2013) emphasizes, the extent of market integration tends to decrease during periods of food shortage. Devereux, Sabates-Wheeler and Longhurst (2011) have revived recently interest in the topic.
gap. It increases supply immediately after the harvest and increases market demand several months later.

Food consumption may also vary seasonally. It can be intentional, reflecting preferences for consumption at one time of the year rather than another, for example linked to religious holidays (Christmas, Ramadan). Often, it has also been linked to seasonality in prices or food availability (depending on the price elasticity of demand) (Dercon and Krishnan 2000). This is especially plausible in low income developing countries where staple foods make up a large share of food consumption and where efficient capital markets or other community-level coping mechanisms are still mostly absent so that households are unable to fully smooth their consumption throughout the year (World Bank, 2014).

Yet studying seasonality is empirically challenging. Sufficiently long seasonal time series data are typically unavailable. Even with a monthly price series of 10 years, there are in effect only 10 observations to discern the recurring month effects from the observed intra-annual fluctuations (and not 120). As a result, seasonality estimates, which often rely on a measure of the difference between the highest and lowest month effects, may be unduly influenced by irregular price movements. This holds especially when the seasonal patterns are a priori unclear and the peak and trough months are inferred from the data. Samples of monthly or seasonal household (food) consumption are usually even shorter (often only spanning one or two years), and if available, limited to case study areas. This makes it even harder to distinguish regular seasonal patterns from random intra-annual variation and to generalize beyond the study area.

This study contributes in three ways. First, methodologically it shows that, when seasonal patterns are absent or unclear and samples short, trigonometric seasonality models can significantly reduce the upward bias in seasonality estimates derived from more commonly used models with monthly dummies. Second, it adds a series of new, robust and comparable estimates of food price seasonality based on the more recent experience. Finally, it provides

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3 In areas where much food consumption is own production and where there is a large wedge between purchase and sale prices, the seasonal pattern in food consumption may even reflect seasonality in food availability rather than prices.
empirical insight in the extent to which food price seasonality transmits into seasonality in food consumption. With the notable exception of Dercon and Krishnan (2000) for Ethiopia, there remains little systematic information on the magnitude of these links.

The empirical application is to Tanzania, which provides a good backdrop to study seasonality in prices and consumption.\(^4\) It covers a wide array of agro-ecological settings and cropping systems and staples (maize and rice) still make up a sizeable share of food consumption (33 percent in rural and 28.5 percent in urban areas). Seasonality in maize and rice prices is estimated from 19 years of monthly prices collected during 1995 and 2013 from 20 regional markets across Tanzania. To estimate seasonality in consumption, three waves of a nationally representative household consumption panel survey are used. The surveys were conducted throughout the year on each occasion starting in 2008-09 and subsequently in 2010-11 and 2012-13. The data enabled identification of the staple price effects on food consumption and simulation of the extent of price induced seasonality in calorie consumption, alongside a household fixed effect estimation strategy and controlling for other consumption seasonal factors.

The results show that the seasonal gap in staple prices is substantial in Tanzania, though variable across markets. It is almost twice as high for maize (27 percent, averaging across districts), as for rice (15 percent). It is also 2.5 to three times more than the gap observed in reference markets (10.7 percent in the South African Futures Exchange market for white maize; and 5 percent broken rice in Bangkok), suggesting substantial excess seasonality. The contribution of seasonality to overall price volatility is limited (13.1 percent for maize and 7.1 percent for rice). Price induced seasonality in caloric intake is sizeable among poor urban households and rural net food sellers (around 10 percent). No effects were discerned among net food buyers.

In what follows, section two shows how commonly used methods of estimating seasonality can yield substantial upward bias on short samples and how this can be reduced by modeling

seasonality through a trigonometric specification. The price seasonality results are in section 3 and section 4 presents the findings on seasonality in food consumption and the link with seasonality in prices, including across different locations and socioeconomic groups (asset poor and rich; net staple buyers and sellers). Section 5 concludes.

2 Characterizing seasonality

Seasonality refers to more or less regular movements through the year in the item under consideration. While such movements may take any form in principle, as when religious or secular holidays are important, it is reasonable to expect the main seasonal movements in food prices and consumption to be related to the production cycle (i.e. regular weather and climatic changes throughout the year). When the focus is on a specific commodity with a single annual harvest, storage costs will dictate that, if no other factors intervene, the price is lowest immediately after the harvest and that it will then rise steadily throughout the crop year to reach a maximum immediately before the next harvest (Samuelson, 1957). Looking across different crops, seasonality is best characterized by crop type and location (geographic and national).

An important statistical problem that arises in analyzing seasonality is to disentangle seasonal movements from the longer term trend in prices or consumption on the one hand and from irregular movements on the other. This problem is acute when the number of data points is small, putting a premium on parsimony in the specification. A second statistical problem is that data series are often incomplete. These elements are discussed in turn.

A common approach to characterizing seasonality in the development literature is to estimate 12 monthly seasonal factors (normalized to 11 when the factors are constrained to sum to zero) in an unrestricted, non-parametric manner. The estimates of these factors are obtained by averaging monthly deviations from an estimated trend, with the trend typically estimated by a 12 month centered moving average (Allen, 1954; Goetz and Weber, 1986). Algebraically, let \( p_{ym} \) be the level of the variable of interest in month \( m \) of year \( y \) and \( \bar{p}_{ym} \) the estimated trend (e.g. in the price or consumption level). The logarithmic seasonal factors \( s_m \) are estimated as:
where \( Y \) is the number of years of data available.\(^5\)

A parametric alternative (adopted by Sahn and Delgado (1989)) is to estimate the seasonal factors and trend jointly from a dummy variables regression with a deterministic time trend:

\[
\ln p_{ym} = \kappa + \sum_{j=1}^{11} \delta_j z_{mj} + \gamma t_{ym} + \varepsilon_{ym} \tag{2}
\]

where \( z_{mj} \) is the dummy variable defined by \( z_{mj} = \begin{cases} 1 & j = m \\ 0 & j \neq m \end{cases} \) and the time trend \( t_{ym} = 12^* (y - 1) + m \). Normalizing \( \delta_{12} = 0 \) to give seasonal factors

\[
s_m = \delta_m - \frac{1}{12} \sum_{j=1}^{12} \delta_j = \delta_m - \bar{\delta} \quad (m = 1, \ldots, 12) \tag{3}
\]

Here, the time trend is given by \( \ln \tilde{p}_{ym} = \kappa + \bar{\delta} + \gamma t_{ym} \).

In principle, the non-parametric (1) method and the parametric regression based alternative (3) will give similar seasonality estimates. Yet, price series in developing countries have often missing values. The dummy variables regressions (2) can be performed skipping over the missing data points. The moving average trend estimation procedure requires that the missing values be interpolated prior to estimating the seasonal factors. Interpolation can introduce bias in the estimated seasonal factors even if equation (1) is modified to skip the missing data points. This, together with the easy availability of regression software, have resulted in the dummy variables regression approach becoming standard.

\(^5\) The symbol \( \approx \) implies that the two expressions are equal to a first order approximation. For simplicity of exposition we suppose data are available for complete years.
The linear trend model defined by equation (2) supposes that the series under investigation is trend-stationary, i.e. that prices revert to a deterministic trend. However, even if price series are trend-non-stationary, they will generally be difference stationary (Nelson and Kang, 1984). In this case, we obtain the stochastic trend model – see Stock and Watson (2003, chapter 12). This suggests a modification to the dummy variables equation to give

\[ \Delta \ln p_{ym} = \gamma + \sum_{j=1}^{11} \delta_j \Delta z_{mj} + v_{ym} \]  

(4)

where the trend price is now defined by \( \ln \hat{p}_{ym} = \ln \hat{p}_{y,m-1} + \gamma \) where \( \gamma \) is the constant drift and where we adopt the convention \( p_{y0} = p_{y-1,12} \).

The deterministic trend model is a special case of the stochastic trend model in which the trend innovation variance is zero. Regression estimates of the coefficients in equation (4) will remain unbiased if the trend is deterministic even though coefficient standard errors will be contaminated by serial correlation induced by over-differencing. The presence of both seasonality and missing prices complicates standard unit root test procedures used to detect whether the trend is deterministic or stationary. To ensure that differences in seasonality estimates are driven by the data and not by model specification, a common model is preferred for the entire set of price series. Below, the stochastic trend model is used to estimate seasonality in prices.

A key attraction of the unrestricted dummy variable regression approach is that no a priori structure is imposed on the form of seasonality. It can, for instance, accommodate crops in which there are two annual harvests. The disadvantage is that a long time series is necessary to obtain accurate estimates since only a single observation per year is used to estimate each seasonal factor. This is especially problematic when the extent of seasonality is measured as the seasonal gap, which is common in this framework⁶ – see Dostie, Haggblade, and

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⁶ In the public health literature it is also common to use the Gini coefficient (Rau, 2005).
Randriamamonjy (2002) and Orr, Mwale and Saiti-Chitsonga (2009). The seasonal gap measure is calculated as the difference between the highest and lowest seasonal factor:

\[ \text{gap} = \max_{m} s_m - \min_{m} s_m \tag{5} \]

In statistical terms, this is a range. Although the estimates of the 12 seasonal factors themselves are unbiased, the range is a nonlinear function of these seasonal factors and so will potentially be biased. Bias arises if large irregular movements confound identification of the peak and trough months. This is more likely when samples are short. This bias would not occur if it is known a priori that the seasonal peak is in month \( a \), say, and the trough is in month \( b \) since the difference \( S_a - S_b \) is the unbiased difference between two unbiased statistics.

Monte Carlo results indicate that the dummy variable procedures to characterizing seasonality perform poorly for samples up to 20 years with irregular variations. They frequently suggest the existence of seasonality which is in effect absent in the data generating process (Table 1, columns 1-2).\(^7\) With no seasonality genuinely present and using 10 years of data, the average estimated seasonal gap is 10 percent using the dummy variables approach, while in effect it is zero.\(^8\) In addition, these spurious seasonal factors purport to explain an average of 9.2 percent of the sample price variability (\( R^2 = 0.0925 \)). A more extended set of simulations, reported in Gilbert, Christiaensen and Kaminski (2015) indicates that large biases also persist in cases in which the seasonality is present, but not well-defined. Series of 10 to 15 years of food price data are common in African samples. The series used here has 19 years of data.

This weakness of the common dummy variable approach to characterizing seasonality can be mitigated by using a more parsimonious, but more restrictive functional approach to characterizing seasonality, such as the trigonometric functions. Ghysels and Osborn (2001) provide a general discussion of trigonometric representations of seasonality. Here, a pure

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\(^7\) The experiments estimate seasonal factors from data where no seasonality is present employing 5, 10, 20 and 40 years of data. They are based on 10,000 simulations.

\(^8\) The bias and \( R^2 \) for each of the simulations are very similar when using the moving average deviation approach to estimate the seasonal gaps (equation 1).
cosine function is pursued. The simplest two parameter trigonometric seasonality representation is:

\[ s_m = \alpha \cos\left(\frac{m\pi}{6}\right) + \beta \sin\left(\frac{m\pi}{6}\right) = \lambda \cos\left(\frac{m\pi}{6} - \omega\right) \]  

(6)

where the seasonal amplitude \( \lambda = \sqrt{\alpha^2 + \beta^2} \) and \( \omega = \tan^{-1}\left(\frac{\alpha}{\beta}\right) \) measures the phase of the seasonal cycle, i.e. the location of the peak and trough. The analogue of the seasonal gap is \( 2\lambda \) but since \( \omega \) will not in general refer to an integer number of months, this quantity will typically slightly exceed the gap as measured by equation (4). Although least squares estimates of \( \alpha \) and \( \beta \) are unbiased, \( \lambda \) and \( \omega \) are nonlinear functions of these unbiased estimates and are therefore potentially biased.

In conjunction with a stochastic trend, the seasonal parameters \( \lambda \) and \( \omega \) may be estimated from the linear regression:

\[ \Delta \ln p_{ym} = \gamma + \alpha \Delta \cos\left(\frac{m\pi}{6}\right) + \beta \Delta \sin\left(\frac{m\pi}{6}\right) + \nu_{ym} \]  

(7)

There is no requirement to interpolate over missing data.

Columns 3 and 4 of Table 1 repeat the Monte Carlo experiments using the trigonometric estimator defined by equation (5). The price data are exactly the same as those used in analyzing the dummy variables. For all sample lengths, the bias in the estimates of the seasonal gap is reduced by just under 40 percent relative to the dummy variables method. The degree of “explanation” provided by seasonality is reduced even more substantially. This gives some confidence that the trigonometric specification provides a more reliable means of representing seasonal patterns on short data samples.

**Seasonality in consumption and its link with prices**

In principle, similar procedures can be followed to examine seasonality in food consumption. Ideally, as with prices, this requires long time series data on daily or monthly food consumption...
for each individual or household. Such data are not available in most countries (and surely not in Africa). Lacking this information, some inferences can still be made about the degree of seasonality from nationally representative integrated household consumption surveys, such as the Living Standard Measurement Studies. At a minimum, repeated cross sectional surveys are needed that are each time conducted throughout the year, so that a representative sample of households is interviewed in each month of the year.

Let \( m_{hw} \) be the month number (January = 1, February = 2, etc.) in which household \( h \) was interviewed in wave \( w \) and \( c_{hw} \) food consumption per equivalent adult of household \( h \) in wave \( w \). The seasonal factors of consumption can then be estimated as:

\[
\ln c_{hw} = \kappa_w + \delta^j z_{hw} + \gamma^j x_{hw} + \eta_h + \varepsilon_{hw}
\]  

(8)

With \( \kappa_w \) a wave-specific intercept (to capture the wave-specific effects), \( x_{hw} \) a vector of time varying household and environmental characteristics, \( \eta_h \) a household-specific constant and \( \varepsilon_{hw} \) a disturbance. The variables of interest are the eleven seasonal variables \( z_{hwj} \) \((m = 1, \ldots, 11)\) defined by

\[
z_{hwj} = \begin{cases} 
1 & m_{hw} = j \\
0 & \text{otherwise} 
\end{cases} \quad (j = 1, \ldots, 11)
\]

The vector of seasonal factors \( s \) derives from the estimated \( \delta \) coefficients using equation (3) and the seasonal gap follows from equation (5).

The seasonal factors can in principle be obtained by estimating (8) through pooled OLS (i.e. setting the household-specific constants \( \eta \) to zero). Two concerns deserve attention. First, if the interview months are not random (for example if poorer and more remote areas tend to be surveyed towards the end of the wave) and heterogeneity across households is not fully controlled for by the vector of control variables \( x \), then pooled OLS estimates of the seasonal factors may be biased. Household fixed effects estimation can mitigate these concerns (by controlling for all time invariant variables affecting both the month of interview and

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consumption). This requires panel data. For this to work, interview months must also differ across waves for a sufficient number of households since otherwise the effect of the month of interview cannot be identified. While less prone to bias, fixed effects estimation comes at the expense of precision, making it a more stringent test of seasonality. The availability of three waves of household panel data in Tanzania, each conducted throughout the year and with many households interviewed in different months across waves, enables this study to follow the fixed-effects estimation route.

Second, seasonal factors are estimated on a limited number of observations for each month (three in the empirical application of this paper). The Monte Carlo results presented above in connection with price seasonality indicate that seasonal gaps estimated in short time series may be biased upwards. It is reasonable to suppose that this result will extend to panels with short time dimension. The more parsimonious trigonometric specification is therefore also explored here:

$$\ln c_{hw} = \kappa_w + \alpha \sin \left( \frac{m_{hw} \pi}{6} \right) + \beta \cos \left( \frac{m_{hw} \pi}{6} \right) + \gamma' x_{hw} + \eta_h + \varepsilon_{hw}$$  \hspace{1cm} (9)

Fixed effects estimation of (9) is the preferred specification. For comparison, the estimated seasonal gap using the dummy variable approach (with and without fixed effects) will also be reported. To control for sources of consumption seasonality that are unrelated to the production cycle, such as the effect of specific demand shifters related to religious events and holidays (e.g. Ramadan and Christmas), a December dummy, to account for possible additional Christmas expenditure, and a Ramadan dummy are added to the vector of controls $x_{hw}$.

Finally, understanding the extent to which seasonality in food prices transmits to seasonality in food consumption is the third core question of interest. It is natural to suppose that seasonality in food consumption is a consequence of seasonality in the prices of subsistence foods – see Dercon and Krishnan (2000), Dostie, Haggblade, and Randriamamonjy (2002) and Ellis and Manda (2012). High food prices generate both negative income and substitution effects for net food purchasers. For net food sellers, greater price seasonality induces larger fluctuations in income. A larger share of their income depends on food production and their sales are often
concentrated right after the harvest. This is the channel emphasized by Khandker (2012) and Bellemare, Barrett and Just (2013) in studying the welfare loss from food price seasonality and volatility.

An indicative answer to the question of price induced seasonality in food consumption is given by the seasonal gap in consumption obtained from estimating (9), at least to the extent that the estimated seasonality related to the monthly fluctuations in consumption can be attributed to movements in the prices of food staples. Controlling for possible demand shifters such as the religious holidays in the estimation of the seasonal factors makes this plausible. Nonetheless, it cannot be excluded that other factors, unrelated to staple prices, are driving the results. Also, the very limited number of observations for each month, remains a concern. If unobserved common factors have affected food consumption in a particular year across an entire sample or sub-sample, this may give rise to misleading seasonality estimates when samples are short. Examples of such factors in the Tanzanian data include increasingly severe drought conditions during the 2008-09 LSMS-ISA wave and severe flooding which may have impacted December and January food consumption in the 2010-11 wave. Inclusion of household fixed effects does not control for the effect of such unobserved time variant factors.

To address these difficulties the effect of staple prices on food consumption is estimated directly, conditioning on the month of interview and religious holidays (i.e. conditioning on other potential sources of seasonality in food consumption). In particular, equation (9) is extended to:

$$\ln c_{hw} = \kappa_w + \theta \ln p_{hw}^{av} + \alpha \sin \left( \frac{m_{hw} \pi}{6} \right) + \beta \cos \left( \frac{m_{hw} \pi}{6} \right) + \gamma' x_{hw} + \eta_h + \epsilon_{hw}$$

(10)

The price-based seasonal factors for food consumption are then given by the seasonal factors in the average price series $p^{av}$ multiplied by the estimate of the price elasticity $\theta$. Given that the price seasonal factors are obtained from longer time series market data (19 years in the case of Tanzania), they will be less subject to the short sample bias problems which potentially affects the consumption seasonality estimates of equation (8). By controlling for the month of interview and religious events, the estimated price elasticity is also purged from other seasonal
factors affecting consumption. To explore heterogeneity in the elasticity of food demand to staple prices and thus the effect of staple price seasonality on food consumption, the caloric price elasticity is estimated separately for poor and rich urban and rural households, with rural households further divided in (poor and rich) net staple buyers and (poor and rich) net staple sellers.

Two qualifications remain. First, seasonal movements in food prices have only formed a small proportion of overall food price variability over the period analyzed. If households respond more to large price movements than to small movements, the effects of seasonality on caloric intake will be over-estimated. A quadratic specification of prices will be tested. Second, it is possible that households respond more to price changes that are seen as permanent relative to those such as seasonal movements, seen as transient. Again this can lead to an over-estimation of the seasonal impact of prices on food consumption. To explore robustness of the findings, prices will be split into a seasonal and a desesasonalized component and the equality of both coefficients will be tested.

The food consumption variable can be represented using spatially and intertemporally deflated food expenditures or using caloric intake. The latter variable gives a more direct estimate of changes in consumption quantities and nutritional outcomes. They are the preferred measure here. Many rural households are food producers and for these households a proportion of food expenditure will be imputed from self-consumed quantities. Even though imputed prices are derived from other household purchases and quantities in the same period and location/region, which vary across districts, this complicates matters, as it introduces potential endogeneity by having prices in the dependent and independent variables.

3  **Staple prices display substantial excess seasonality in Tanzania**

White maize is the most important staple food product in Tanzania (as in most of eastern and southern Africa). In rural areas it accounts for 50.6 percent of spending on staples and 26.3
percent of spending on food. In urban areas, the shares are 35.0 and 15.1 percent respectively. Rice is also an important staple in urban centers (31.1 percent of spending on staples, and 13.4 percent of spending on food), but less so in the countryside (13.3 percent of spending on staples). The focus is on seasonality in maize and rice prices and whether this translates into seasonality in caloric intake. Bananas and cassava account on average only for 3.6 and 6.5 percent of total food spending among rural households (even less among urban households).

Monthly maize and rice price series from 20 regional markets in mainland Tanzania during 1995-2013 (all regional capitals) were obtained from the national statistical offices. Prices are expressed in local currency and deflated by the national CPI. If the data set had been complete, there would have been 228 observations for each market (or 4,560 observations in total). Overall, 6.3 percent of the maize prices are missing and 5.4 percent of the rice prices, indicating that the prices are relatively complete. More than half of the markets are almost complete (more than 220 observations out of a maximum of 228). However, for some markets less than half of the possible observations are available, with minimums of 84 (maize) and 105 (rice). This underlines the importance of using a procedure for estimating seasonal impacts which is robust to the presence of these gaps.

For comparison purposes, seasonality in international prices for white maize and rice is also analyzed. The Johannesburg futures market (SAFEX) provides the reference price for white maize in southern and east Africa. This price is quoted in rand. For rice, the most commonly used reference price is the Bangkok spot price which is quoted in US dollars. Monthly SAFEX

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10 Staples comprise all cereals, tubers and starchy products whether consumed crude or processed. They include wheat, rice, sorghum, millet, maize, cooking bananas, Irish and sweet potatoes and yams. Pulses (beans, peas and oilseeds such as groundnuts) are not included. Shares are calculated from the Tanzania (2008-2009) LSMS-ISA household survey.

11 In a companion paper, Gilbert, Christiaensen and Kaminski (2015), provide a systematic analysis of the extent of price seasonality across an array of staple and non-staple food and food products in seven African countries.

12 Price seasonality estimates using nominal prices are very similar.

prices series for white maize were obtained for the period March 1996-December 2012; monthly Bangkok rice prices for 2000-2012.  

Tanzania is a large country exhibiting significant differences in climate and terrain across regions. Reflecting these differences, the estimated seasonal patterns for each market differ both in amplitude (and hence gap size) and phase (seasonal peak and trough dates) (Figure 1). Comparison of a seasonal model (trigonometric or dummy), with a model without seasonality, using the Bayesian (Schwartz) Information Criterion (BIC) which penalizes excess parameterization, confirms seasonality in 19 of the 20 markets for maize and 16 of the 20 markets for rice (Table 2, column 1). Comparison of the trigonometric with the dummy variable approach further shows that trigonometric model is preferred in most markets (17 out of 19 for maize and in all markets for rice). This provides confidence in the use of the more parsimonious trigonometric model pursued here. The dummy specification is preferred for both the SAFEX and Bangkok exchange prices.

Maize prices are on average 26.6 percent higher during the peak month than during the trough (Table 2, trigonometric specification (column 6)). The seasonal price gap for maize in Tanzania is sizeable. It is also almost twice as large as the gap for rice (15.2 percent on average). Rice is a tradable product, although Tanzanian rice imports remain small, and as a product consumed predominantly in urban areas, it is subject to lower intermediation costs. The estimated gaps based on the dummy variable approach are slightly higher (30 and 17.8 percent on average for maize and rice respectively) (Table 2, column 5). This is consistent with the Monte Carlo results, which suggest a slight upward bias for 20 year samples, if there are no or unclear seasonal patterns in the underlying data generating process.  

There is also substantial variation in the

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15 As Gilbert, Christiaensen and Kaminski (2015) show, when the samples are shorter and seasonal patterns are less clear as in many other countries and crops, the dummy variable approach tends to generate sizably larger seasonal gap estimates than those obtained through the trigonometric specification. A referee suggested that we should set the seasonal factors to zero in those cases in which the F tests fail to reject the hypothesis of no seasonal variation. Such non-rejections are consistent either with an absence of seasonality or with insufficient evidence in the data to support the claim that the series is seasonal. Setting the seasonal factors to zero in cases where these are positive but statistically insignificant would bias the estimate of the average seasonal factors towards zero.
seasonal gaps across locations, ranging from 13.6 percent to 46.5 percent for maize and between 3.0 percent and 22.0 percent for rice (Figure 2).

Seasonality in the international prices is estimated at 10.7 percent for SAFEX white maize and 4.7 percent for Bangkok rice. These findings underline that some degree of price seasonality is to be expected, even when markets function efficiently. Second, seasonality of international maize prices is also about twice as high as this of rice, providing confidence in the domestic findings. Finally, the Tanzanian maize and rice seasonal price gaps are on average 2.5 to three times higher than those observed in the international markets, with the gap substantially above the international one in virtually all markets. This points to substantial excess seasonality in Tanzania’s staple markets.

Finally, the seasonal $R^2$ statistics (Table 2, column 7) show that only 13.1 percent the monthly variation in maize and rice prices is attributable to seasonality. For rice, this is about half (7.1 percent). Seasonality does not appear to be a major contributor to staple price volatility. While there will benefits from reducing seasonal price fluctuations of staple foods to enable households to better smooth their consumption expenditures, policies aimed at this objective will not substitute for policies addressing the overall level of food price volatility.

4  **Staple price induced seasonality affects poorer urban households and net food sellers**

The data on consumption and other household characteristics are from the three available Living Standard Measurement Study-Integrated Surveys on Africa (LSMS-ISA) waves for Tanzania (2008-09, 2010-11 and 2012-13). These are panel datasets in which considerable effort is made to recontact households which relocate between waves as well as to track the components of the households which break up or combine, generating in effect a panel of individuals. See [www.worldbank.org/lsms-isa](http://www.worldbank.org/lsms-isa) for details. The analysis is confined to the

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16 When using the dummy variable approach, the shares are about twice as high (22.6 and 15.2 percent for maize and rice respectively), overestimating the contribution of seasonality to price volatility by a factor two.
mainland regions of Tanzania to conform to the price analysis reported in section 3. The LSMS-ISA surveys covered 4,232 mainland Tanzanian households in 2008-09, 4,241 households in 2010-11 and 4,215 households in 2013-14.

Interviews took each time place over a 14 month period within the two year survey window, with the majority of households surveyed within the 12 month period of that year. Very few interviews took place in either the first month (September 2008) or the final month (October 2009) of the initial wave. The second two waves had full initial months but a relatively small number of interviews in the final one or two months (October and November 2011 and November 2013). Pearson $\chi^2$ tests reject randomness of the interview months over regions.$^{17}$ This is remedied through the inclusion of household fixed effects and inclusion of time varying household characteristics, including the asset level of the household (as a proxy for wealth), household size (persons, not adult equivalents), the sex and education level of the identified head of household, a rural-urban dummy and dummy variables for region of residence and survey wave.$^{18}$

Households were not generally interviewed in the same month in each wave. This is partly due to inter-regional movements and partly due to changes in the interview months for households that remained in the same region. 5.3 percent of households crossed regional boundaries between the first two waves and 6.8 percent did so between the second and third waves. 55.2 percent of households that remained in the same region were interviewed in the same calendar month in the 2008-09 and 2010-11 rounds and 40.3 percent were interviewed in the same month in the 2010-11 and 2012-13 rounds. Only 20.5 percent of households that remained in the same region for all three waves were interviewed in the same calendar month in all three waves. These features of the data ensure that the month of interview is a time-varying variable permitting the estimation of seasonal effects using the FE estimator.

$^{17}$ The $\chi^2(260)$ were in excess of 4500 for each of the three waves.

$^{18}$ Household size is the number of household members. The number of equivalent adults gives a poorer fit. The rural-urban dummy distinguishes rural from “other urban” households outside Dar es Salaam which is regarded as entirely urban and which is accounted for by one of the regional dummies.
The proportion of the interview month which lies within the Ramadan period which is defined by the Islamic lunar calendar is also controlled for. Ramadan advances through the calendar underlying the LSMS-ISA data with the consequence that lunar seasonality may confound the solar seasonality reflected in the crop year and food prices. Many urban households return to their villages at Christmas and it is plausible that this results in higher caloric intake at that time. This departure is controlled for by including a dummy variable which takes the value one if the household was interviewed in December. The seasonality observed in food consumption is reported net of these confounding effects. Caloric intake is obtained by converting reported food expenditures or food quantities from the expenditure module into calories. Food expenditures and intake are reported at the household level for the past 7 days.

Columns 1 and 2 in Table 3 report the pooled OLS estimates of equations (8) and (9) respectively (for comparison). The pooled OLS estimates indicate significant seasonality. The trigonometric specification is preferred over the dummy variable approach (lower BIC). Figure 3 charts the dummy variable (solid line) and trigonometric (broken line) seasonal factors from pooled OLS. The dummy estimates show caloric intake to be low from November to January and high from March to June with an estimated seasonal gap of 10.6 percent. The estimated trigonometric factors are (inevitably) much smoother. Relative to the dummy estimates, they give a lower estimate the depth of the November and January troughs but also the extent of the March to May recovery. The vertical bars in Figure 3 show the 95% confidence intervals for the dummy variable seasonal factors. November is the only month in which this confidence interval excludes zero. Although the trigonometric factors are generally much lower than the dummy variable estimates, there is only one month (again November) in which the trigonometric estimate falls outside the 95% dummy variable confidence intervals.

The FE seasonality estimates are reported in columns 3 and 4 of Table 3. The dummy variable specification does not show significant seasonality, unlike the more parsimonious

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19 The choice between pooled OLS and the FE estimator involves balancing possible inconsistency arising from unmodeled household heterogeneity and loss of information in the FE estimation procedure. The information loss results in two ways. First, the FE transformation results in a loss of approximately one third of the observations through differencing or by taking deviations about household means. Second, the data are only informative about seasonal effects for those household who were interviewed in different months in at least one of the three waves.
trigonometric specification (which is also preferred by the BIC criterion). Figure 4 plots the two seasonal functions together with the 95% confidence range for the dummy variable estimates. The trigonometric seasonal functions (which omit the large December effect given the inclusion of the December dummy) are again much shallower than the visual pattern suggested by the dummy variable seasonal factors. In this case, both the trigonometric seasonality function and the zero axis lie entirely within the 95% dummy variable confidence intervals. The estimated seasonal gap based on the trigonometric specification is 2.7 percent.

Three conclusions emerge. First, the F tests reject the hypothesis of no seasonality in caloric intake. This is true of both sets of pooled OLS estimates and of the FE trigonometric estimates. Second, on average, across Tanzania, seasonality in food consumption appears limited. Third, notwithstanding these insights and the large cross-section dimension of the dataset, measuring consumption seasonality from only three cross-sections of data remains ambitious and indicative at best. It also does not tell us whether the observed seasonality in food consumption is due to seasonality in staple prices, which the paper now probes further by estimating the elasticity of calorie consumption to staple prices.

The focus in estimating the elasticity of calorie consumption to staple prices is on the effect of the concurrent price of maize and rice, the two principal staple foods. In particular, an average staple food price \( p^{sv} \) is constructed as the logarithmic average of the deflated maize and rice prices in the district of each reporting household using regionally differentiated expenditure weights, distinguishing across districts and between urban and rural households.\(^{20}\) The Tanzanian maize and rice price series contain gaps, which we interpolate using estimates of equation (4).\(^{21}\)

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Overall, our FE estimates are effectively based on approximately one third of the number of observations used in the pooled OLS estimates implying a substantial loss in efficiency.

\(^{20}\) Price data are not reported for the Pwani region which forms the hinterland to Dar es Salaam. We use Dar es Salaam prices for Pwani households.

\(^{21}\) The procedure for estimating seasonal gaps is robust against the presence of missing values avoiding the need for interpolation at that stage. However, in constructing the average staples prices we have the choice between dropping missing observations and interpolating. In the latter case, we can interpolate using estimates of equations (4). The results are qualitatively similar and in what follows we report the results using interpolated prices. We use equation (4) to construct interpolated prices for region \( r \) over a gap of \( k \) months as
Both the pooled OLS and the FE estimations of equation (9) (which models seasonality trigonometrically) show a statistically significant price elasticity, but the FE estimates are larger (more negative) than those from pooled OLS (Table 4). The estimated seasonal gap of 3.2 percent is correspondingly higher, though still modest in absolute terms. The FE estimates also appear superior from the statistical standpoint. In the remainder, the focus is on the FE estimates. The seasonal and deseasonalized components of staple prices do not show a difference in their effects, removing concerns about potential over or underestimation of price induced seasonality due to differences in the caloric response to regular and irregular price changes. Also, linearity in the price elasticity is not rejected—the coefficient on squared prices is insignificant.

The results in Table 4 are based on a representative national sample. They show a modest price-induced seasonal gap in caloric intake, averaging across the entire Tanzanian mainland. However, households are heterogeneous both in terms of their locations (urban versus rural), wealth levels and, for rural households, also in their net marketing position (net food buyers or net food sellers). We consider a three by two disaggregation distinguishing households resident in Dar es Salaam, which LSMS-ISA regards as entirely urban, other urban households and rural households. Then, within each group we distinguish between asset poor and asset non-poor households. The staple price elasticity is estimated separately for each subgroup (conditional

\[
ln p_{r,y,m+j} = ln p_{r,y,m} + \hat{y} j + \hat{s}, y_{m+j} \quad (j = 1, ..., k)
\]

where hats upper scripts respectively stand for the estimated price seasonal factors and price drift. We further improve on this formulation by taking into account the current period residuals from regions where the data is present: \(ln p_{r,y,m+j} = ln p_{r,y,m} + \hat{y} j + \hat{s}, y_{m+j} + \sum_{j=1}^{r} \hat{b}_{r,s,j} e_{s,j,y,m+j} (j = 1, ..., k)\) where \(s\) is the region in which the residuals from equation (4) are most highly correlated with those for region \(r\) over the subset of observations of which observations are available for both regions and \(\hat{b}_{r,s,j}\) is the simple regression coefficient associated with the maximum correlation. The accuracy of this interpolation will diminish as the gap length \(r\) increases. Omission of all observations involving a missing price implies a fall in the number of observations available for estimation of 6.8 percent for the other urban sub-sample, 9.8 percent for the rural net purchasers sub-sample, and 8.6 percent for the rural net sellers sub-sample. There is no loss for the Dar es Salaam sub-sample. The interpolated prices are used only in estimation of the caloric intake equation (10).

22 The Hausman test rejects equality of the coefficients of the pooled and FE estimators (\(\chi^{2}_{39} = 95.41\) (tail probability 0.0000) when applied to the complete set of coefficients, and \(\chi^{2}_{1} = 16.13\) (tail probability 0.0000) when only the price elasticities are compared).
on other seasonal factors as in equation (10)). Differences in price elasticity among rural net food buyers and net food sellers (poor and rich) are further explored.

The poor are distinguished from the rich using a household asset ownership index. This was constructed by taking the first leading component of household durables ownership. The asset index is constructed separately for each survey wave. A household is classified as asset poor if its asset index is below the median for that group (Dar es Salaam, urban or rural) in each of the waves in which it was surveyed and as asset rich otherwise. This classification puts 31.1% of the households into the asset poor classification and 18.1% into the asset rich classification leaving 50.8% as an intermediate vulnerable group. As noted, these classifications depend on different asset indices in each wave in conjunction with medians that differ across groups. The terms “asset rich” and “asset poor” are therefore relative, not absolute, measures. Net staple food buyers are distinguished from net staple food sellers based on whether the absolute value of the ratio of the difference between their annual staple sales and purchases divided by their total food expenditures exceeds 5 percent as observed in 2008-2009 (Palacios-Lopez, Christiaensen and Galindo Pardo, 2015). Net food buyers make up 78.9 percent, net food sellers 7.2 percent, and the remaining 13.9 percent are marginal market participants, with less than 5 percent net purchases or sales. When we disaggregate, the marginal participants are dropped from the analysis.

At the aggregate level, the price elasticities for Dar es Salaam, other urban and rural households are all negative, but only that for the other urban group is statistically significant at the 5% level (Table 5). The estimated price-induced seasonal gaps are larger for the urban than for the rural areas, and largest for the poor in both urban areas. Yet with sample sizes becoming increasingly small, and estimates still obtained through fixed effect estimation, precision declines. On these estimates, the urban poor group suffers from the largest seasonal calorie gap (between 6.6 and 10.4 percent). By contrast, there is no evidence of price responsiveness of caloric intake on the part of poor rural households in general.

About two-thirds of rural households produce maize, much of it for own consumption. To the extent that maize-producing households retain grain through the year, either domestically or in
local warehouses, this will provide some insulation against seasonal and other price movements. This may go some way to explaining the relatively low estimated price elasticity for rural households. LSMS-ISA breaks down rural households into three groups: net food purchasers, net food sellers and an intermediate group. The two bottom panels of Table 5 report estimates of equation (10) for the net buyer and net seller sub-categories. The number of observations becomes very small, in particular when considering further division into asset rich and asset poor categories. The net buyers are the largest group within the rural classification and the estimates are very similar to those for the entire group. However, the net food sellers are associated with much greater price responsiveness, apparently irrespective of asset level. These findings are consistent with those reported by Khandker (2012) for Bangladesh, i.e. seasonality in food consumption increasing with seasonality in income, with no clear difference in this pattern between poor and non-poor households. Net sellers derive more of their income from crop sales (around 50 percent of total income for rural net sellers versus 35 percent for the rural net buyers), which turns out to be mostly sold in the months immediately after the harvest (Palacios-Lopez, Christiaensen, Galindo-Pardo, 2015), especially within the first three months after harvest. Their incomes are more seasonal as a result. For Ethiopia, Bellamare, Barrett and Just (2013) also find that the willingness to pay for price stabilization is highest among the larger net food sellers.

5 Conclusion

While any knowledgeable observer knows of seasonality in African food markets and consumption, it is much less clear what it is that is actually known. There proves to be surprisingly little systematic evidence across crops, markets and countries about the extent of food price seasonality, how it differs across these crops and markets, how it compares to reference markets, and how it affects household welfare and health outcomes. Moreover, most available studies date from the 1980s and 1990s and they have typically been conducted on

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23 Most maize-producing households retain grain for about six months for food consumption purposes in most cases, After 10 months it is 90 percent depleted (Kaminski and Christiaensen, 2014).

24 Richer rural net sellers manage to spread their sales more evenly over a longer period after the harvest. They also show a lower price elasticity of caloric intake than poor rural net sellers.
short samples. When it comes to consumption, they often having only one year of seasonal data, rendering it impossible to discern regular seasonal patterns from (idiosyncratic) intra-annual variation. This paper revisits this agenda, methodologically and empirically, taking 19 years of food price data over the past two decades and three waves of nationally representative panel data on household consumption over the past decade from Tanzania. Three insights emerge.

First, methodologically, the paper has shown that the most widely used technique of estimating the seasonal gap either from a dummy variables regression or by averaging deviations from a moving average trend can give upwardly biased estimates of the seasonal gap when implemented on samples covering less than 20 years. The bias results when non-systematic high or low prices are mistakenly taken as identifying seasonal peaks or troughs. This problem is particularly severe for crops in which the seasonal pattern is poorly defined. The alternative, trigonometrically based procedure for estimating seasonal factors on short data samples proposed here, gives more reliable results.

Second, the current neglect of price seasonality is premature. Wholesale maize prices are estimated to be 27 percent higher than those during the troughs (on average across the 20 wholesale markets). The seasonal gap is about half as large for rice (15 percent), which is partly irrigated and more widely traded. Seasonality explains 7 to 13 percent of overall price volatility (for rice and maize respectively), underscoring that many other sources of domestic food price volatility remain. Nonetheless, seasonal variation is 2.5 to three times larger than on the international reference markets (SAFEX for white maize and Bangkok for rice). This suggests substantial scope for improved access to secure storage and other measures to reduce seasonality, even more so when targeted to those markets displaying the highest seasonal gaps. Across markets in the country, they vary between 13 and 46 percent for maize and between 3 and 22 percent for rice, indicating substantial heterogeneity in food price seasonality across the country.

Third, there appears price-induced seasonality in caloric intake (controlling for other seasonal factors), though not for everyone. When taken on average across the country, seasonality in
food prices induces only a 3.2 percent seasonal gap in caloric intake. However, the extent of this seasonal variation varies substantially across households. Two groups suffer most – poorer urban households and rural net food sellers. Both see seasonal swings in caloric intake of about 10 percent, linked to seasonality in maize and rice prices. These variations occur at low levels of caloric intake and do not account for intra-household distribution. Substantial detrimental effects on child malnutrition from food price seasonality cannot be excluded. Rural net food buying households, who form the largest group in the country, appear to be able to largely smooth their caloric intake across the crop year.

Together these findings suggest that, while seasonal price variation is not a major contributor to food price volatility, the issue of seasonality remains relevant for African livelihoods, despite larger domestic market integration and two decades of economic growth, structural transformation and urbanization, and poverty reduction. Seasonal variation in staple prices is substantially larger than on the international markets, which is consistent with the view that storage is inefficient and points to the need to improve farm- and village-level storage, among others. Turning to food consumption, the evidence suggests that households who are net food buyers do not experience major problems with intra-annual consumption smoothing. This does not imply that they are unaffected by high food prices but, on average, they do appear to be able to cope with regular seasonal price variations. Poor urban households and net food sellers suffer from much greater seasonal consumption variation.

From a broader measurement perspective, the findings underscore the need to account for seasonality in prices and consumption in measuring poverty. The importance of doing so has been illustrated before by Muller (2008), but remains largely ignored in practice (Beegle, Christiaensen, Dabalen and Gaddis, 2016). With many of our results, especially on consumption, based on a short sample and one country, replication and extension of the findings using longer time periods and across different settings is important to strengthen their internal and external validity. New waves of the LSMS-ISA surveys in Tanzania and other countries are now becoming available, opening up exciting opportunities to do so, including along a wider range of welfare indicators and indicators of longer term impacts such as child growth and nutrition.
References


Table 1
Monte Carlo estimates of seasonality biases

| Years | Dummy variables | | Trigonometric | |
|-------|-----------------|-----------------|
|       | Bias $R^2$      | Bias $R^2$      | |
| 5     | 0.142 0.187     | 0.088 0.034     | |
| 10    | 0.100 0.093     | 0.062 0.017     | |
| 20    | 0.071 0.046     | 0.044 0.008     | |
| 40    | 0.050 0.023     | 0.032 0.004     | |

The table reports the estimated seasonal gap from seasonal estimation procedures when the data are non-seasonal, and the apparent degree of explanation provided by these estimates. Price changes are normally and independently distributed with mean and variance equal to 0.01. There is no seasonality and no trend. Columns (1) and (2) use regression (4) with the seasonal gap measured by equation (5). Columns (3) and (4) use equation (7) with the seasonal gap measured by $2\lambda$. Estimates are based on 10,000 simulations.
<table>
<thead>
<tr>
<th></th>
<th>Locations</th>
<th>Seasonality confirmed</th>
<th>Preferred specification</th>
<th>Estimated seasonal gap</th>
<th>Seasonal $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Trigonometric</td>
<td>Dummy</td>
<td>Trigonometric</td>
</tr>
<tr>
<td>Maize</td>
<td>Tanzania</td>
<td>20</td>
<td>19</td>
<td>17</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>SAFEX</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Rice</td>
<td>Tanzania</td>
<td>20</td>
<td>16</td>
<td>16</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Bangkok</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

Dummy variable seasonal gaps are estimated from equations (4) and (5); trigonometric seasonal gaps are measured from equation (6) and (7). In both cases, (simple) national averages of location seasonal gaps are reported. Seasonality is “confirmed” in a location if the BIC associated with either the dummy or the trigonometric specification is lower than on an equation with no seasonality. The “preferred” of the dummy and trigonometric specifications for locations in which seasonality is “confirmed” is that with the lower BIC. The seasonal $R^2$ is the proportional of the monthly price variation explained by seasonality, averaged across all locations.
### Table 3

#### Unconditional caloric intake seasonality estimates

<table>
<thead>
<tr>
<th></th>
<th>Pooled OLS</th>
<th>Fixed Effects</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Dummies</td>
<td>Trigonometric</td>
</tr>
<tr>
<td>Significance</td>
<td>$F_{11,12310} = 3.50^{***}$</td>
<td>$F_{3,12318} = 6.52^{***}$</td>
</tr>
<tr>
<td></td>
<td>[0.0001]</td>
<td>[0.0002]</td>
</tr>
<tr>
<td>BIC</td>
<td>1.5007</td>
<td>1.4961</td>
</tr>
<tr>
<td>Seasonal gap</td>
<td>10.3%</td>
<td>6.1%</td>
</tr>
</tbody>
</table>

The table reports the estimates of equations (8) (columns 1 and 3) and (9) (columns 2 and 4). Columns 1 and 2 report pooled OLS estimates and columns 3 and 4 FE panel estimates. The Bayesian Information Criterion (BIC) is on a per observation basis. For each estimator, the lower BIC value is favored. It each time favors the trigonometric specification. The seasonal gap is calculated using equation (5) in columns 1 and 3 and as $2\lambda$ in columns 2 and 4. The estimates in columns 2 and 4 exclude any December effect. Tail probabilities are reported in square parentheses and robust t statistics in round parentheses. The symbols *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively.
Table 4
Aggregate price-based caloric intake seasonality estimates

<table>
<thead>
<tr>
<th></th>
<th>Pooled OLS</th>
<th>FE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price elasticity $\theta$</td>
<td>-0.0890**</td>
<td>-0.1477***</td>
</tr>
<tr>
<td></td>
<td>(2.49)</td>
<td>(3.83)</td>
</tr>
<tr>
<td>Significance of trigonometric variable coefficients $\alpha$ and $\beta$</td>
<td>$F_{2,12316} = 9.26^{***}$</td>
<td>$F_{2,4245} = 0.32$</td>
</tr>
<tr>
<td></td>
<td>[0.0001]</td>
<td>[0.7275]</td>
</tr>
<tr>
<td>Nonlinearity</td>
<td>$F_{1,12315} = 4.13^{**}$</td>
<td>$F_{1,4245} = 2.46$</td>
</tr>
<tr>
<td></td>
<td>[0.0421]</td>
<td>[0.1169]</td>
</tr>
<tr>
<td>Persistence</td>
<td>$F_{1,12315} = 2.97^{*}$</td>
<td>$F_{1,4245} = 0.17$</td>
</tr>
<tr>
<td></td>
<td>[0.0850]</td>
<td>[0.6838]</td>
</tr>
<tr>
<td>BIC</td>
<td>1.4971</td>
<td>0.9207</td>
</tr>
<tr>
<td>Seasonal gap</td>
<td>2.0%</td>
<td>3.2%</td>
</tr>
</tbody>
</table>

The table reports the estimates of equation (9) using pooled OLS (column 1) and Fixed Effects (Fe, column 2).

The nonlinearity test adds the squared price to the equation and tests for its significance.

The persistence test splits the price into a deseasonalized component and the seasonal. It tests for equality of the two coefficients.

The Bayesian Information Criterion (BIC) is on a per observation basis. These values should be compared with the BICs for the same estimator reported in Table 3.

The seasonal gap is calculated by multiplying the estimated price elasticity and the seasonal gap in the price series $\rho_{hw}^{av}$, averaged across all households. It excludes December and Ramadan effects.

Tail probabilities are reported in square parentheses and robust $t$ statistics in round parentheses. The symbols *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively.
Table 5
Disaggregated price responsiveness of caloric intake and implied seasonal gaps

<table>
<thead>
<tr>
<th></th>
<th>Observations</th>
<th>price elasticity</th>
<th>trigonometric variables</th>
<th>average seasonal gap</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dar es Salaam</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All</td>
<td>2044</td>
<td>-0.1614 (0.95)</td>
<td>$F_{2,820} = 3.16^{**}$</td>
<td>2.9%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-0.5714 (1.47)</td>
<td>$F_{2,820} = 4.13^{**}$</td>
<td>10.4%</td>
</tr>
<tr>
<td></td>
<td>610</td>
<td>0.0218 (0.06)</td>
<td>$F_{2,226} = 0.79$</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>569</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Other urban</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All</td>
<td>2264</td>
<td>-0.2516 (2.41)</td>
<td>$F_{2,1040} = 2.37$</td>
<td>5.2%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-0.3183 (1.44)</td>
<td>$F_{2,477} = 1.18$</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>789</td>
<td>0.1947 (1.07)</td>
<td>$F_{2,231} = 3.01^*$</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>499</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All rural</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>poor</td>
<td>8048</td>
<td>-0.0824 (1.84)</td>
<td>$F_{2,3005} = 4.41^{**}$</td>
<td>1.9%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-0.0832 (0.98)</td>
<td>$F_{2,912} = 0.50$</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>2461</td>
<td>0.1973 (1.07)</td>
<td>$F_{2,438} = 1.81$</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>1152</td>
<td></td>
<td>$F_{2,2200} = 8.75^{***}$</td>
<td>-</td>
</tr>
<tr>
<td>Rich</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rural net buyers</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All</td>
<td>5751</td>
<td>-0.0832 (1.59)</td>
<td>$F_{2,866} = 1.04$</td>
<td>1.9%</td>
</tr>
<tr>
<td></td>
<td>1764</td>
<td>0.0394 (0.38)</td>
<td>$F_{2,671} = 1.06$</td>
<td>3.8%</td>
</tr>
<tr>
<td></td>
<td>875</td>
<td>-0.1678 (1.43)</td>
<td></td>
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<tr>
<td>Rural net sellers</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All</td>
<td>844</td>
<td>-0.2463 (1.98)</td>
<td>$F_{2,291} = 0.60$</td>
<td>5.6%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-0.4700 (1.86)</td>
<td>$F_{2,78} = 2.06$</td>
<td>10.8%</td>
</tr>
<tr>
<td></td>
<td>234</td>
<td>0.3496 (0.97)</td>
<td>$F_{2,35} = 0.02$</td>
<td>8.0%</td>
</tr>
<tr>
<td></td>
<td>103</td>
<td></td>
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</tbody>
</table>

Column 2 of the table reports the price elasticity obtained from Fixed Effects (FE) estimates of equation (10). The number of observations is measured prior to application of the FE transformation. Column 3 reports the Wald test for exclusion of the two trigonometric seasonal variables. $t$ and $F$ statistics are based on robust estimates of the variance-covariance matrix. The seasonal gap reported in column 5 is the seasonal gap in the price variable multiplied by the price elasticity. Because both prices and the relative maize-rice weight varies across districts, the gap will also vary across districts for “other urban” and rural households. We report the simple average of the gaps across the twenty districts excluding Dar es Salaam. The split of the rural sample into net food buyers and net sellers excludes a middle category. * *, ** indicate significance at the 10%, 5% and 1% levels respectively.
Figure 1: Estimated trigonometric maize price seasonality patterns, Tanzania
Figure 2: Estimated seasonal gaps
Figure 3: Pooled OLS seasonal functions for caloric intake
Figure 4: Panel Fixed Effects seasonal functions for caloric intake