The End of Seasonality?

New Insights from Sub-Saharan Africa

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ABSTRACT:

Seasonality has disappeared from Africa's development debate. In food prices, the focus has been on volatility, ignoring the predictable (seasonal) component. Information on intra-annual fluctuations in household consumption is even harder to come by. This paper revisits the extent of seasonality in African livelihoods. First, econometric analysis of monthly food price series across 100 locations in 3 countries during 2000-2012 shows that seasonal movements in maize wholesale prices explain 20 (Tanzania, Uganda) to 40 (Malawi) percent of their monthly volatility. Monthly maize peak prices are on average 30 (Tanzania, Uganda) to 50 (Malawi) percent higher than their monthly troughs and two to three times higher than the seasonal gaps observed for white maize at the South African Futures Exchange. Second, household food consumption inversely tracks food prices in each country, decreasing when staple prices increase; increasing when they decline. (Excess) seasonality in African food markets and consumption persists, necessitating policy attention.

JEL: D12, D14, D40, D91, I31

Keywords: maize, seasonality, Sub-Saharan Africa, food and non-food consumption

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1 Introduction

Seasonality (in food prices and consumption) was much studied in the nineties and shown to be associated with significant intra-annual fluctuations in welfare, with a focus on food security and nutrition (Sahn 1989). Since then, the topic has largely disappeared from the policy debate as well as in project design and the academic literature (Devereux, Sabates-Wheeler and Longhurst, 2011).

The general perception of improved integration of local food markets may have partly motivated the neglect.[2] But 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 in neighboring countries).[3]

Second, seasonality may also be a non-negligible component of food price volatility. The latter has attracted a lot of attention since the 2007-8 global food price crisis (Galtier and Vindel, 2012; World Bank, 2012a), as uncertainty might hamper the much needed supply response. But not all price volatility is stochastic and uncertain. And, to the extent that volatility follows from predictable, intra-annual, i.e. seasonal, price movements, a different policy response is needed. Because seasonal patterns are regular and repeated over time, we can quantify the contribution of seasonality to overall volatility.

To be sure, a certain degree of seasonality in food prices is unavoidable. As production is cyclical, intertemporal arbitrage is needed and storage costs ensue, driven by post harvest loss and

[2] Araujo and Araujo–Bonjean (2008) document better domestic integration of the millet markets in West Africa and Aker and Fafchamps (2014) discuss how better mobile phone coverage in Niger decreased the intra-annual price dispersion for cowpeas. The latter authors also highlight that this is not automatic and that the impact of the technology can differ substantially by type of crop (semi-perishable or storable) and agent (consumer, trader, or producer), and the time during the year, even within the same country. Studying maize markets in Malawi during 1999-2009, Zant (2013) also cautions against the perception of full market integration, as the probability of integrated markets consistently and substantially decreases during periods of food shortages, when trade is most needed.

[3] Trade between countries with less (positively) correlated food production cycles would help reduce food storage costs, which is an important reason for seasonality in food prices (Dana, Gilbert, and Shim, 2006). Recent studies suggest however that food markets in Africa are often still poorly integrated across countries, even if they may be better integrated within countries (Araujo and Araujo-Bonjean, 2008; and Araujo, Araujo-Bonjean, and Brunelin, 2012 for millet in West Africa; Ihle, von Cramon-Taubadel, and Zorya, 2010 for maize in East Africa; Daviron, 2008; World Bank, 2012b).

the opportunity cost of capital.[4] This drives a wedge between prices before and after the harvest. This price gap can be compounded by market power along the marketing chain and in storage (Osborne, 2004; 2005), by high transaction costs (due to poor infrastructure, fuel costs (Dillon and Barrett, 2013) or transport monopolies (Teravaninthorn and Raballand, 2009))[5], and by credit constraints for traders. Imperfect capital markets may also induce sell-low, buy-back-high behavior among liquidity constrained households (Stephens and Barrett, 2011). This may further push up the seasonal price gap, as supply increases immediately after the harvest, while demand increases in the face of limited supply, just before the new harvest arrives.

Under certain circumstances, seasonal price variability may also translate into seasonal variation in (food) consumption.[6] When capital markets fail, and other coping mechanisms such as community-level risk-sharing arrangements, counter-seasonal income generation through off-farm employment or migration, are not available or inadequate to cope with (co-variant) fluctuations in food prices, households may no longer be able to smooth their consumption throughout the year, resulting in welfare loss. Seasonal movements in non-food consumption may be larger than those in food. The latter is more price-inelastic, and households may thus attempt to smooth their food intake by adjusting non-food consumption first.

Against this background, this paper systematically revisits the question of seasonality in Sub-Saharan African livelihoods. To do so, it examines the extent of seasonal patterns in food prices as observed during 2000-2012 across 100 market locations spread across three countries (Malawi, Tanzania, and Uganda) for a range of food products. Differently from most of the development economics literature, it also controls for price trends using time series econometric methods

[4] Price seasonality may also follow from seasonal patterns in demand such as those related to festivities, e.g. high sugar demand in preparation of the Eid festival or high demand for pork to celebrate the China's lunar New Year.

[5] With high transaction costs, trade becomes an imperfect substitute of storage for producers (Williams and Wright, 1991).

[6] Dercon and Krishnan (2000), Dostie, Haggblade, and Randriamamonjy (2002); Ellis and Manda (2012). In contrast to these studies from Sub-Saharan Africa, Khandker (2012) finds a decline in food consumption in Bangladesh when rice prices are lowest, because income during this period declines even faster. In the absence of good mechanisms to smooth income households see their food purchasing power in effect decline, as the decline in seasonal income is larger than the decline in the staple price, resulting in a rising ratio of the rice price over monthly income.

common in the study of finance. The paper subsequently maps out the intra-annual monthly variation observed in food and non-food consumption in nationally representative household consumption surveys that have been conducted throughout the year in each of these three countries around 2009. The fact that each month, a nationally representative slice of the population has been surveyed, makes this possible and has been exploited here, even though each of the households has only been surveyed once. Finally, in a first descriptive, exploratory step, the seasonal evolution of the country's (weighted) staple food prices is juxtaposed against the intra-annual variation of consumption to explore connections between intra-annual patterns in staple food price movements and consumption.

While essentially descriptive in nature, this paper fills an important empirical void in the current understanding of the evolution of food prices and consumption across seasons. By using time series econometrics to control for price trends, by systematically looking across different food crops, markets (wholesale and retail) and agro-ecological settings in three different countries and using nationally representative household living standard measurement surveys from each of these countries, it updates and enriches the existing literature, which is too often confined to studying seasonality in one country, or even case study areas within a country, and typically relies on unconditional estimates of seasonality, with only few recent studies also linking the current intra-annual evolution of food prices in Africa to this of household consumption.[7] An update on the extent of seasonality in African livelihoods also helps guide the renewed public and private policy and investment interest in African agriculture.

The econometric analysis of monthly food price series shows that seasonal movements in maize wholesale prices explain 20 (Tanzania, Uganda) to 40 (Malawi) percent of their monthly volatility, and between 15 to 20 percent for other crops (Tanzania). Peak prices for wholesale maize are on average 30 (Tanzania, Uganda) to 50 (Malawi) percent higher than their monthly troughs and two to three times higher than the seasonal gaps observed for white maize at the South African

[7] Chirwa, Dorward and Vigneri (2009) provide a useful exception for Malawi.

Futures Exchange (SAFEX), suggesting high and excess seasonal sensitivity for the key staple in these countries. The seasonal gaps are lower (15 to 25 percent) for other staple cereals, consistent with their greater integration in the international markets (rice) and better storability (millet and sorghum). Juxtaposition of the seasonal evolution of the weighted staple price index against the (weighted) monthly fluctuation in food and non-food consumption, further suggests that household food consumption closely tracks staples prices in each of the three countries, decreasing when staple prices increase; increasing when they decline. Seasonality continues to permeate African food markets and much of their livelihoods.

The paper proceeds by discussing first in section 2, how best to measure seasonality, conceptually as well as empirically. Contextual information about the food price data and markets is provided in section 3, together with a review of the consumption measures. The price seasonality measures are then presented in Section 4, including some robustness checks. Section 5 reviews the insights obtained from estimating intra-annual variation in consumption across different settings in the three study countries and the association between food price seasonality and the intra-annual variation in consumption is subsequently explored through juxtaposition. Section 6 concludes.

2 Measuring seasonality – concepts and methods

Seasonality refers to certain regular intra-annual movements of a variable of interest. This could be a price or consumption (the variables of interest here), but it could also concern labor supply patterns, children's or adult health status, fertility behavior, etc. To capture the degree of seasonality, different measures have been proposed, each focusing on different aspects of the intra-annual flow. The development economics literature has typically used a *year-specific* seasonal gap measure, defined as the range between the price immediately prior to the arrival of the new harvest and this prevailing once the harvest is fully in (see for instance Dostie, Haggblade, and Randriamamonjy, 2002; or Orr, Mwale and Saiti-Chitsonga, 2009). This measure works well for crops where there is a single annual harvest but is less useful in more complex environments. Year-specific seasonal gaps exhibit considerable year-to-year variability. Both demand shocks and developments on world markets can have the result that the price peak or trough may fall in the middle of a crop year. Furthermore, the crude gap measure fails to allow for trend or autocorrelation issues and can be distorted by large irregular movements which may coincide with seasonal peaks or troughs.

The seasonal gap is a range measure of variability. The price volatility literature typically looks at the standard deviation of price returns– see, for example, Gilbert and Morgan (2010, 2011). The standard deviation reflects variability throughout the crop year whereas the gap takes only the two extreme observations into account. If intra-annual prices were normally and independently distributed, a simple relationship would exist between these two measures (Parkinson, 1980). That assumption is implausible and in practice the two measures respond to different questions. In the context of a crop for which there is a single harvest and where imports are difficult, intra-annual price variability will be dominated by the fall in price as the new crop becomes available. With two harvests or continuous harvesting, there may not be a regular and dominant price movement with the implication that the intra-annual price standard deviation gives a superior measure of seasonal price variability.

The public health literature uses the Gini coefficient to measure seasonality (Rau, 2005). It could be adapted to measure the seasonal inequality of consumption levels.[8] The Gini inequality measure compares each expenditure level with each other expenditure level. It may be rationalized in terms of the Strong Principle of Transfers which underlies inequality measures (Cowell, 1977) which requires, in this context, that a transfer from a high to a low consumption month should reduce seasonal inequality.[9] The Gini therefore responds to the question, "To what extent would

[8] Given a set of estimated proportionate seasonal factors s_m such that expected consumption in month m is $\overline{c}\left(1+s_m\right)$. Re-order the seasonal factors such that $s_{(1)} \le s_{(2)} \le \ldots \le s_{(12)}$. The seasonal Gini may be calculated as

$$Gini = \frac{\sum_{m=1}^{12} m\overline{C}\left(1+s_{(m)}\right)}{6\sum_{m=1}^{12}\overline{C}\left(1+s_{(m)}\right)} - \frac{13}{12} = \frac{1}{72}\sum_{m=1}^{12} m\left(1+s_{(m)}\right) - \frac{13}{12} = \frac{1}{72}\sum_{m=1}^{12} m s_{(m)}$$

[9] Proportionate transfers are not mean-preserving and hence do not meet the Principle of Transfers.

seasonal inequality be reduced, on average over time, by a transfer of consumption from a high to a low month?" Provided the seasonal factors are estimated either unconditionally (from weighted average consumption levels across households by months or specific time periods) orby regression, an aggregate seasonal Gini will disaggregate into the average seasonal Gini over households.

The Gini seasonal inequality measure compares consumption in each month with consumption in all other months and is thus dependent on the entire distribution of seasonal effects. Instead, the seasonal gap, $\max\{s_m\} - \min\{s_m\}$, depends only on the two most extreme consumption levels. The gap measure only satisfies the Weak Principle of Transfers since it will be unaffected by a consumption transfer which does not involve the two extreme months. Nevertheless, a transfer to one of the hungry pre-harvest months may be precisely the transfer of greatest interest. The notion of transfers only applies directly to quantities. The Gini measure therefore is not easily interpretable as a measure of price seasonality.

The paper opts to stay within the tradition of the development economics literature and focuses on the seasonal gap as main measure of seasonality, given the direct link of our variables of interest (prices and consumption) with seasonality in agricultural production, and given the straightforward interpretation of the gap measure. For consumption, the seasonal Gini () coefficients are presented for comparison.[10] Importantly, the paper goes beyond the more traditional (unconditional) monthly averages of prices (or consumption) and uses a seasonal gap estimate derived from time series of multiple years of monthly observations conditioning on the trend and other time series features, where the data allow it. These measures differ from year-specific gaps in measuring regular seasonality and are as such more general.

To fix ideas, let P be a price time series and p be the corresponding log price series, $p = \ln P$. Seasonal effects are generally proportionate rather than absolute—higher at times of high prices than when prices are low—so it makes sense to analyze the logarithms of prices rather than their

[10] Analysis of the standard deviations in prices did not yield different insights (available upon request from the authors).

levels. In what follows, the data are taken to be monthly. Refer to the price observation in month m of year y as p_{my} or as p_t depending on the context, $t = 12(y - y_0) + m$, where y_0 is the initial year of the sample. Unconditional seasonal factors result either from averaging prices over months or by regressing on a set of dummy variables.[11] Averaging, one obtains $s_m = \frac{1}{n}\sum_{y=1}^{n}(p_{ym} - \overline{p})$ where $\overline{p} = \frac{1}{12n}\sum_{y=1}^{n}\sum_{j=1}^{12} p_{yj}$, the overall sample mean and n is the number of years in the sample. The unconditional seasonal gap is then just $gap = \max(s_m) - \min(s_m)$.[12]

Food price and expenditure data typically trend and this is true of the data analyzed here. The trend may reflect cyclical or secular changes in production or consumption or may result from inflation. Deflation of food prices to obtain real prices is dangerous if food comprises a large proportion of the consumption basket and may distort or eliminate the seasonal features of the data which are of interest. Therefore, nominal (local currency) prices are used here. In a sample covering only a small number of years, any trend in prices will be positively correlated with the seasonal dummy variables—a positive trend will be positively correlated with the dummies for later months and negatively correlated with the earlier dummies. Failure to control for the trend will result in omitted variable bias in the seasonal components. It is therefore desirable to control for the trend in estimating the seasonal components. Even in a longer sample, where the omitted variable bias will be negligible, controlling for the trend will give more precise seasonality estimates.

Detrending involves an implicit or explicit trend model. There is a danger that the choice of model may affect the resulting seasonality estimates. To minimize the judgmental element in this process, a very general estimation model is proposed:

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[11] The same estimates are obtained by regression of the demeaned vector p on the eleven seasonal dummies (but no intercept). Suppose the twelfth dummy is omitted and write the coefficients of the dummy variables as the vector b. The mth centered seasonal component is then $s_m = b_m - \frac{1}{12}\sum_{j=1}^{11} b_j$ where $b_{12} = 0$.

[12] An alternative approach would be to calculate gaps for each year and average these. The annual gaps calculated in this way are intra-annual ranges. They tend to be an order larger than seasonal gaps since irregular movements can result in the highest or lowest prices in a year occurring at times other than the immediate pre- and post-harvest months.

$$p_t = \mu_t + s_t + \varepsilon_t \tag{1}$$

where μ is the trend – see Harvey (1989). In the most general case, the trend is generated as a random walk with stochastic drift δ,

$$\begin{aligned} \mu_t &= \mu_{t-1} + \delta_t + \nu_t \\ \delta_t &= \delta_{t-1} + \upsilon_t \end{aligned} \tag{2}$$

where ε, ν, and υ are mutually independent innovational disturbances. In order to ensure serial independence, it is useful to add a set of *k* autoregressive lags to equation (1)

$$p_t = \sum_{j=1}^{k} \gamma_j p_{t-j} + \mu_t + s_t + \varepsilon_t \tag{3}$$

In the empirical applications below, setting $k = 2$ appeared sufficient to generate serially independent residuals. Ignoring the seasonal components, the model defined by equations (2) and (3) may be rewritten as an ARIMA(2,2,2). In very many cases, the drift δ turns out to be constant, i.e. $\mathrm{Var}(\upsilon_t)$ is estimated at its boundary value of zero. In that case, the specification becomes equivalent to an ARIMA(2,1,1). If, in addition, $\mathrm{Var}(\nu_t)$ is estimated as zero, the trend becomes deterministic, $\mu_t = \mu_0 + \delta t$ and the model is an ARIMA(2,0,0).

The seasonal component *s* in equation (3) can be estimated from a set of eleven dummies (footnote 11). Alternatively, the seasonal pattern may be re-expressed as a sum of trigonometric functions. The trigonometric representation allows the possibility of estimating a smaller number of parameters in which case a smoother seasonal representation may emerge. The trigonometric representation of the seasonal component for month *m* of year *y* is

$$s_{ym} = \sum_{j=1}^{6} \sigma_{jm} \quad \text{where} \quad \sigma_{jm} = \alpha_j \cos\left(\frac{jm\pi}{6}\right) + \beta_j \sin\left(\frac{jm\pi}{6}\right) \tag{4}$$

where $\beta_6 = 0$ (since $\sin(2\pi) = 0$) – see Ghysels and Osborn (2001). With monthly data, the six seasonal cycles have periods of 12, 6, 4, 3, 2.4 and 2 months respectively.[13]

[13] If there is a single harvest and trade is unimportant, seasonality can be well represented by the initial (12 month) cycle. In that case, the seasonality takes the form of a pure sine wave

The trigonometric representation is also convenient in terms of its flexibility in accommodating time-varying seasonality. Symmetrically with the trend representation in equation (2), one can allow the eleven α and β coefficients to evolve over time as $\begin{pmatrix}\alpha_t\\ \beta_t\end{pmatrix}=\begin{pmatrix}\alpha_{t-1}\\ \beta_{t-1}\end{pmatrix}+\zeta_t$ where ζ is an 11-vector of independent innovations. In terms of the general specification (4), this may be shown to be equivalent to the Harvey (1989) representation

$$\begin{pmatrix}\sigma_{jm}\\ \sigma^*_{jm}\end{pmatrix}=\begin{pmatrix}\cos\left(\frac{jm\pi}{6}\right) & \sin\left(\frac{jm\pi}{6}\right)\\ -\sin\left(\frac{jm\pi}{6}\right) & \cos\left(\frac{jm\pi}{6}\right)\end{pmatrix}\begin{pmatrix}\sigma_{j,m-1}\\ \sigma^*_{j,m-1}\end{pmatrix}+\begin{pmatrix}\zeta_{jt}\\ \zeta^*_{jt}\end{pmatrix}\quad (j=1,\ldots,6) \tag{5}$$

where σ^* denote virtual conjugate processes, the 6-vector ζ is a seasonal innovation process and ζ^* is its virtual conjugate with $\text{Var}(\omega_{jt})=\text{Var}(\omega^*_{jt})$.[14] Harvey (2006) argues that, in practice, very little is lost by additionally imposing $\text{Var}(\omega_{jt})=\text{Var}(\omega_{1t})\quad(j=2,\ldots,6)$ so that the variation in the seasonals is accounted for by a single additional parameter. This is the approach adopted in the estimates that follow. Estimations are done using the STAMP package (Koopmans et al, 1999).

The conditional seasonal gap estimate is obtained as (max (s_t) - min(s_t)) obtained from the STAMP procedure.[15] To calculate the contribution of seasonality to overall price volatility, (3) is deseasonalized, giving $\tilde{p}_t=\sum_{j=1}^{k}\gamma_j p_{t-j}+\mu_t+\varepsilon_t$. Because the trend is the dominant component,

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

where $\lambda=\sqrt{\alpha^2+\beta^2}$ is the seasonal amplitude and $\omega=\tan^{-1}\left(\frac{\alpha}{\beta}\right)$ is the phase shift relative to the cycle defined by the cycle $\cos\left(\frac{m\pi}{6}\right)$.[13] If seasonality does have this sinusoidal structure, the seasonal gap is approximately λ.

[14] The conjugate process reverses the sign of one of the components (here the sine function) in the process of interest. Use of the conjugate notation allows expression of a cyclical second order difference equation in σ_{jm} as a first order process in the vector $(\sigma_{jm}\sigma^*_{jm})'$.

[15] For those crop-location pairs for which seasonality is variable, the seasonal gap is measured in 2012 which is the final year of the sample.

$sd(\Delta p_t)$ and $sd(\Delta \tilde{p}_t)$ are compared, eliminating trend movements. The result is that the resulting seasonal $R^2 = 1 - \left(\frac{sd(\Delta \tilde{p}_t)}{sd(\Delta p_t)} \right)^2$ is a measure of the contribution of seasonality to volatility rather than to variability above a trending mean – see Gilbert and Morgan (2010, 2011).

Seasonality in food (and non-food) consumption can be analyzed in a similar manner. Write the level of consumption in period *t* (month *m* of year *y*) as $C_t = C_{ym}$ with year *y* mean $\overline{C}_y$. As before, the conditional seasonal gaps can be calculated either from the level or the log data. Yet data on consumers' expenditure are generally only available on an annual basis in developing countries and hence are uninformative in relation to seasonality. In some cases, households are surveyed two, three or occasionally four times in a year, but even if so, they would only give a bi-annual or quarterly (and not a monthly) picture and rarely are such surveys repeated over several years, especially not in Sub-Saharan Africa (Garcia-Verdu, 2014). Several years of surveys are necessary to identify a true, seasonal pattern, as opposed to the intra-annual variation observed in one year, which comprises both the seasonal patterns as well as the year specific deviations from it.

Such data constraints are common to most studies on consumption seasonality in the literature and as most of these studies, this paper also only has one (Malawi, Uganda) or two years of consumption data (Tanzania), allowing it to paint a snapshot of intra-annual variations in household consumption, as opposed to true seasonal variations. The latter represent regular monthly deviations from the annual average observed across many years. Differently from most other studies, estimates of the monthly deviation from the annual average could be obtained in this case, by exploiting the fact that a nationally representative sample of the population was surveyed in each country. To do this, the following model was estimated:

$$\ln C_{imy}^{f/nf} = \boldsymbol{\beta}^{\mathbf{f/nf}} \mathbf{X_{iy}} + \mathbf{S_m^{f/nf}} + A_{iy}^{f/nf} + \varepsilon_{imy}^{f/nf} \qquad (6)$$

where *f/nf* upper script stands for food or non-food, *i* denotes the household, *m* and *y* the month and year of the interview, $\mathbf{X_{iy}}$ is a matrix of household characteristics that do not vary across seasons (including rural/urban and regional indicator variables), $\mathbf{S}_{\mathbf{m}}^{\mathbf{f/nf}}$ is a vector of month dummies (capturing the month of interview), $A_{iy}^{f/nf}$ is a dummy which is equal to one when household has been interviewed in a new agricultural season (compared with the agricultural season during which the bulk of the sample has been interviewed)[16], $\boldsymbol{\beta}^{f/nf}$ is a vector of control regressors to be estimated, and $\varepsilon_{imy}^{f/nf}$ is an error term. The equations were estimated using sampling-weighted OLS, with the estimated coefficients on the monthly dummies the estimates of interest.

Before bringing (6) to the data, a number of considerations are in place. While under certain circumstances, seasonality in (food) prices may induce seasonal variations in consumption, consumption seasonality may also follow directly from seasonality in income flows (Khandker, 2012), or seasonal patterns in spending, such as the need to pay school fees/uniforms at the beginning of the school year, or increased spending on clothing during certain festivals. As the different consumption components are typically collected with different recall periods (last seven days for food expenditures, last seven days, month or year for non-food expenditures), and subsequently annualized, great care is needed in constructing the consumption variable for seasonality analysis as well as the interpretation of the coefficients on the monthly dummies.

First, if certain expenditures are concentrated in specific months (e.g. schooling expenses) and only asked about for the past month, the seasonal effect would be rightly attributed to that month, but overestimated (because it would have been annualized, i.e. multiplied by 12). If the same question had been asked with a recall period of a year, no month or seasonal effects should be observed, unless there is a retrospective bias. In our data, he latter appears to be the case for spending on education and small appliances. While the amount of spending on these items was sought on an annual recall basis, they nonetheless displayed substantial monthly variation.[17] We therefore omitted these components of expenditures from the consumption aggregate. While this

[16] In some cases, the surveys spanned more than 12 months, thereby capturing the beginning of the next agricultural season.
[17] No major change in education policies was observed during the period of the survey.

may lead to a slight underestimation of seasonality in non-food consumption, the core interest here is in exploring the intra-annual variation in food consumption, whose fluctuations are most detrimental to welfare.

Second, a substantial part of food consumption in developing countries typically comes from own production. Auto-consumption was valued at the median unit value for that item obtained from the same enumeration area at the same month. If insufficient observations were available to obtain a unit value for that food item for that month within the same enumeration area, median values were obtained from higher levels (district, regions, national). All values of food and non-food sub-aggregate components have subsequently been spatially and intra-annually deflated (i.e. expressed in the prices of one region-month). Expenditures are thus expressed in real terms, and intra-annual fluctuations can be interpreted as changes in (aggregate) quantities.

Turning to the survey design, even though the samples were drawn to be nationally representative per period, slight deviations may have been introduced during survey implementation for practical purposes, to accommodate the survey teams. To control for differences in the composition of the samples across periods that may have been introduced in this way, seasonally invariant household and location characteristics ($\mathbf{X}_{iy}$) were added in equation (6). These include the education, sex, and age of the household head, plus agro-economic zone and regional controls.[18] Robustness of the seasonal gap estimates was further checked against specifications without regional dummies and/or without accounting for sampling weights and survey strata.

Finally, heterogeneous timing in seasonality across locations may attenuate the intra-annual variation when the estimation is on the national samples. Therefore, the seasonal factors are estimated from the national sample, but also separately for regional sub-samples. Urban, Northern,

[18] The inclusion of other common controls (such as household size, income, assets) was avoided, because as exhibiting mild seasonality themselves. Note that the primary purpose at this junction is not to explain the reasons for intra-annual variation in consumption (e.g. due to seasonality in prices or income), but rather to document the degree of intra-annual variation in consumption itself, and the inclusion of seasonally varying controls would lead to an underestimation of the intra-annual variation in consumption, as they may pick up some of the intra-annual variation. This was confirmed in robustness test regressions that also included household size, income, and assets (not reported, but available upon request).

Central, and Southern rural sub-samples were distinguished in Malawi, as the crop calendar differs by latitude – see FAO (2004). Urban, rural areas with a single harvest and rural areas with two harvests were distinguished in Uganda and Tanzania.

3 The information base

Monthly price series for a wide array of staple and non-staple crops and food products in wholesale and retail markets during 2000-2012 were obtained from national statistical offices (Malawi and Tanzania) and a private marketing agency (Uganda). Eight markets were covered in Uganda, twenty in Tanzania and seventy-two in Malawi. Monthly prices were collected on between five (Malawi) and twenty-three (Uganda) food products, including maize, rice, millet and sorghum, beans, cassava (the key staples), groundnuts, and some vegetables and fruits (e.g. tomatoes and bananas). Special attention will be given to maize (the main staple crop – see Table 1 below), with the others acting as comparators. Vegetables and fruits are for example highly perishable and their prices are thus expected to much more seasonal. For a number of products both wholesale and retail prices were collected (though not in Malawi). Together this yielded a total of 890 crop-market price series (Table 1). The prices are all expressed in nominal terms and in local currency.

Less than 5% of the price data points used in the estimation was missing, and to work with the longest possible time series, these data points were imputed following Gilbert (2010a). In particular, when there is a month for which prices are available for at least 50% of the marketplaces, the median price[19] across all non-missing values for available marketplaces for each commodity in the same country is calculated, as well as the margin between the actual marketplace values and the median for all non-missing values of that particular month. This margin is then estimated as a second order auto-regressive pooled OLS across months and marketplaces for each commodity. The

[19] The median is used to avoid undue influence from extreme observations. It is also less affected than the mean by missing values.

predicted values from the auto-regressive OLS are added to the monthly median to impute missing prices.[20]

The evolution of the median monthly maize wholesale price across all markets for each country is depicted in Figure 1. The series display high volatility, especially since the second half of the 2000s. Visual inspection further suggests that there is some annual regularity (i.e. seasonality) in these price series, with the seasonal pattern in Uganda (which is above the equator) often the reverse of this in Tanzania (below the equator)—when the median monthly price peaks in Tanzania, it tends to bottom out in Uganda, and vice versa. Seasonal price movements in Malawi (also below the equator) are similar to those in Tanzania.

Table 2 reports statistics on other variables of interest, the monthly average of food and non-food consumption obtained from the three Living Standard Measurement Studies-Integrates Surveys on Agriculture household survey datasets collected in Malawi (2010-11), Tanzania (2008-09 and 2010-11) and in Uganda (2009-10). For a detailed description of these surveys, including on the construction of the consumption aggregates, see www.worldbank.org/lsms-isa. The key issues related to the construction of the consumption aggregates and how these may bear on the estimation of intra-annual variation from these cross-sections have already been discussed above.

The consumption aggregate comprises four main components: food, non-food, durable goods, and housing, with the latter three merged in a non-food sub-aggregate. The food sub-aggregate is constructed by summing the reported consumption of all food items (between 120 and 150 organized in 11 categories depending on the country) across all household members present during the past seven days, and using the last seven days as the recall period.

Expenditures on non-food, and semi-durables were collected with different recall periods (over the last week for utilities such as oil, gasoline, or electricity, public transportation, and

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[20] The formal imputation formula writes the same for each commodity separately as (for all locations *i* and month t): $\ln p_{it} = \overline{\ln p_t} + \widehat{\ln p_{it} - \overline{\ln p_t}}$ where $\widehat{\ln p_{it} - \overline{\ln p_t}}$ is predicted by the pooled OLS regression: $\ln p_{it} - \ln \overline{p_t} = a + b_1(\ln p_{it-1} - \overline{\ln p_{t-1}}) + b_2(\ln p_{it-2} - \overline{\ln p_{t-2}}) + e_{it}$ and where the last term is a normally and i.i.d residual term. In the small numbers of cases in which all prices are missing for a particular commodity-country pair, the values are imputed by the STAMP Kalman filter.

communications; over the previous month for expenses on mobile phones, personal care (health), and recreation; over the past three months for expenses on clothing; and the past twelve months for expenses on furnishings, small appliances, and education (including fees, meals, and lodging/boarding).

All expenditures were converted into annual figures (as for the food items) with a region-specific intra-annual deflator depending on the recall period, location (by stratum), and the month of interview to make them comparable with one another at the reference month of the survey. Some non-food items were excluded, in particular payment of mortgages or debts (financial transactions), losses to theft, remittances and expenditures on marriages, dowries, births, and funerals (too sporadic).. Finally, the non-food sub-aggregate also incorporates an imputed value of the stream of services accruing to households from ownership of durable goods (between 20 and 30 depending on the survey round and country, but excluding productive assets) and housing.

Survey coverage was reasonably even across months (Table A1), though coverage was smaller in month three and four in Tanzania. Sampling weights were adjusted accordingly and non-seasonal household and location characteristics were included to control for possible sample heterogeneity among the monthly sub-samples. The table provides descriptive statistics on these variables.

Reviewing the simple monthly sample averages of the real food and non-food expenditures, converted to constant PPP-adjusted 2005 USD, suggests substantial intra-annual variation (Table 2), with food expenditures in the highest months 25 (Tanzania) to 43 (Malawi) percent higher than those in the lowest months. The gaps are even higher for non-food expenditures (though the base is also lower). Given that it concerns only one year, year specific deviations, as well as seasonality, may underpin these gaps. Nonetheless, the consistency of the pattern across the three countries suggests a substantial degree of recurrent intra-annual variation.

Table 3 reports food expenditure shares and the shares of the different staples in total staple expenditures. The food expenditure shares vary slightly across months (consistent with the larger seasonal gap in non-foods). Maize and rice make up the bulk of staple consumption in Malawi and Tanzania, while starchy foods (cooked bananas and cassava) are equally important in Uganda. But those shares vary within the year given substitution across staples: and especially between cereals and continuously-harvested tubers and starchy food for instance in Tanzania the sum of maize and rice shares vary from 50 to 75% in total within the year.

4 Staple prices display considerable seasonality

In estimating the seasonal components of equation 3, the monthly price time series were found to be all non-stationary, with a stochastic trend and constant drift terms in the majority of the cases (- see Table A2 for test results. For the key staples (maize, rice, cassava and also matoke in Uganda), the seasonal factors are jointly statistically significant across most markets, with the seasonal patterns in these markets typically also constant over time (Table A3). For example, for maize, which makes up between 68 (Malawi) and 20 percent (Uganda) of total staple consumption (Table 3 above), the seasonal factors are jointly statistically significant in virtually all wholesale maize markets (97 percent of the Malawian markets; 90 percent of Tanzania's markets and all of Uganda's markets).

Seasonality was also observed in the majority of the wholesale rice markets, the second most important staple. The seasonal factors are jointly significant in 54, 95 and 75 percent of the wholesale rice markets in Malawi, Tanzania and Uganda respectively. Interestingly, among the three countries, seasonality in the rice market was most prevalent where rice was most important in the diet (Tanzania, 17 percent of staple consumption; 13 in rural areas and 31 percent in urban areas) and less so, where it was less significant (Malawi and Uganda, around 6 percent of staple consumption nationally, and 14 percent in urban areas). The seasonal components are statistically significant in 100 and 37.5 percent of the retail matoke and cassava markets of Uganda respectively, where they each make up about 20 percent of the total staple expenditures. Millet and sorghum are not important in the diets of Tanzania or Uganda, and also tend to display less seasonality in these markets. For beans, 85% of seasonal patterns are statistically significant in Tanzania, 64% in Malawi, and 100% are so in Uganda.

These results for the key staples are quite stark, in particular because the tests have 11 degrees of freedom and may therefore lack power when employed on time series covering only a short number of years (in this case, 11 years or less). Averaging across all commodities, seasonality in wholesale prices is statistically significant at the 5% level in 78% of locations in Uganda, 56% of the locations in Malawi, and 62% of the locations in Tanzania. This difference across countries in statistical significance in part reflects differences in the length of the time series available, which is shortest in Malawi (2005-2012 instead of 2000-2012).

How important are these seasonal movements then in relation to overall food price volatility? Calculation of the R^2 (section 2) suggests that between one and two fifths of the total volatility in monthly wholesale maize prices during the period under study is explained by their seasonal pattern—40 percent in Malawi, 22 percent in Tanzania and 27 percent Uganda. For rice millet, sorghum, beans and potatoes the seasonal share of overall volatility is between 15 and 21 percent (in Tanzania). Clearly, a non-negligible part of the observed food price volatility is deterministic, originating in the domestic markets, and annually recurring. It will not go away, even if prices in the international food markets stabilize, which thus deserves separate attention.

But is the amplitude of the seasonal movements also sizeable? For wholesale maize, the estimated conditional seasonal gaps averaged across markets within each country are between 31 (Tanzania) and 54 (Malawi) percent (Table 4). Or, put differently, the monthly peak price is on average between 31 and 54 percent higher than the monthly minimum price within that country. This is after controlling for trends (including those from inflation). This is substantial.

The estimated conditional seasonal gap for the other cereals (averaged across the markets in each country) is about half that of maize wholesale, between 17 (Uganda) and 22 (Malawi) percent for rice, and around 20 -25 percent for sorghum and millet. This would be consistent with better storability of sorghum/millet (World Bank, 2011) and more steady supplies for rice (through greater reliance on import and the potential of multiple crops per year through irrigation).

The cross-country perspective provides one way to "benchmark" food price seasonality (recall that some seasonality in prices is expected given the production cycle and storage (and/or trade) costs). The second approach to benchmarking is to compare domestic price variability with that on world markets. This is a feasible approach for those food crops which enter into international trade, such as maize and rice. In particular, the 2000-2012 conditional wholesale maize and rice series seasonal factors derived from equation (1) for national average price series[21] can be compared with the seasonal factors derived in the same way for the SAFEX white maize cash price and the Bangkok rice price. SAFEX, which is part of the Johannesburg Stock Exchange, is the leading world futures market for white maize and provides the standard benchmark price for white maize both in South Africa and neighboring countries. Thailand is the leading world rice exporter and the Bangkok price is widely taken as indicating the world rice price.[22]

Comparison of the seasonal factor of the SAFEX maize price with those observed for wholesale maize in each of the three countries, confirms the substantially greater seasonality in the national market price series. They exhibit a seasonal range of 24% in Tanzania (January to August), 26% in Uganda (June to September), and 48% in Malawi (February to May) against a seasonal range of 13% for SAFEX prices (January to July) (Figure 2). Malawi and Tanzania exhibit consistent seasonality which follows that of SAFEX with respective one (before) and two (after) month lags and lagged respective correlations among seasonal factors that are equal or above 90%. There are clearly two price seasons in Tanzania and Malawi, and seasonality appears to be twice as high (three times higher in Malawi) as what is observed at the SAFEX level. Local factors in Tanzania and Malawi appear to amplify seasonal variation on world markets. This suggests considerable scope for reducing

[21] Those are obtained by taking the geometric average of all prices for each month observation across market locations in each country.

[22] Prices are monthly averages in South African rand (maize) and US dollars (rice), converted to local currencies at monthly average exchange rates. Sources: SAFEX (maize) and IMF, *International Financial Statistics* (rice and exchange rates).

seasonal variability. Uganda is a maize exporting country and is more distant from Johannesburg (and being largely above the equator, suggesting a different seasonal production cycle). The seasonal price pattern is quite distinct from that of the SAFEX price and also the patterns in Malawi and Tanzania.

Seasonality is also substantially higher for rice in the three countries considered than on the world market (17% to 33% for wholesale markets and 12% to 16% in retail markets against 6% on the world market) (Figure 3). Uganda, which is a net rice importer, shows the greatest seasonal variability in contrast to Tanzania and Malawi which are both in broad rice balance. Rice prices in Uganda also track Bangkok prices more closely showing a 90% correlation between contemporaneous seasonal factors while the relationship is less tight in Tanzania and Malawi with 50% to 70% correlation.

Moving beyond cereals, the gaps are also sizeable and higher than that of maize for non-seasonal crops (cassava, around 25-30% and matoke around 40-45%), both being important staples in Uganda). Processed products (such as flour) exhibit the lowest seasonality, while fruits (oranges, pineapples) and vegetables (tomatoes, onions), which are much more perishable, show the highest scores. For the limited number of products and countries where they could be compared, the gaps tend to be systematically higher in wholesale than in retail markets (possibly related to lower intermediation costs in retail markets). Differences between conditional and unconditional gaps do not appear systematic.

These rankings hold across countries, suggesting that seasonality largely results from commodity and product-specific characteristics. In addition, there is also substantial within-country heterogeneity across markets, highlighting the role of location, as shown by the within-country standard deviations of the conditional gaps in Table 4. The min-max range for seasonal gaps in wholesale maize prices in Malawi is for example between 26 and 86 percent (see Figure 4). It is between 22 and 58 % in Tanzania and between 15 and 44 % in Uganda.

A detailed investigation of the determinants of price seasonality falls beyond the scope of this paper, but an analysis of variance (ANOVA) applied to the pooled sample of all seasonal gaps, across crops/products, countries, markets and their type—retail/wholesale (Table 5) — can help locate the sources of seasonality and provides a decomposition of heterogeneity in the seasonality of local market prices.

Three-way ANOVA decomposition analysis (including all interaction terms to exhaust all unexplained variation) indicates that the crop-location interaction accounts for the major share of overall heterogeneity ahead of the separate pure crop and location effects (42% versus 38% and 18% respectively). This result suggests that most of the variation in the seasonal conditional gaps depends on the crop concerned, though even for the same crop, seasonality varies quite a bit depending on the location, i.e. crop seasonality is highly location-specific, implying higher seasonal gaps for certain crops but lower gaps for others. Together they explain 90 percent or more of the variation in each country. This highlights that the characteristics of the crop (perishability, price elasticity of demand) and their interplay with the characteristics of the location/market place (accessibility, market size, market structure, which all affect their tradability) are important entry points in studying the determinants of food price seasonality.[23]

Figure 5 charts the crop-specific OLS coefficients from the three-way ANOVA. Relative to the unconditional and conditional estimates reported above in Table 4, this analysis implies an unexpectedly low degree of seasonality for beans and for maize (to a lesser extent) and a high degree of seasonality for matoke, once controlling for location-specific and other market characteristics, as well as product-location interactions. This indicates that maize and beans gaps exhibit more location-specific heterogeneity than other crops and have lower "intrinsic" seasonality than one could infer from the conditional gap estimates. Furthermore, seasonal gaps implied by the ANOVA coefficients for the wholesale markets exceed those on retail markets, by around 3%.

[23] Note also that market type (wholesale more seasonal than retail markets) account for a minor but significant share of heterogeneity, but only through interactions with product attributes, which means that seasonality will differ across market types only for certain products but consistently across locations.

5 Consumption Tracks Seasonality in Staple Prices

The estimated results for the intra-annual variability indicators in consumption (as described in equation (6)) are in Table 6 by sub-region per country.[24] The Wald test of joint significance of the monthly dummies is not rejected in 7 out of the 10 sub-regional regressions for food expenditures and in none of the sub region regressions for non-food expenditures. This suggests that intra-annual variability in household consumption is still quite common across countries and settings within countries, especially for non-food expenditures, but also for food expenditures. Note also that the intra-annual variability is not confined to rural areas but is also observed in urban settings. The estimated intra-annual gaps in consumption between the highest and lowest months can be substantial ranging from 31 (rural south in Malawi) to 82 percent (urban Tanzania) for food expenditures and from 21 (rural south in Malawi) to 233 percent (urban Uganda) for non-food expenditures. Second, they are typically higher in amplitude for non-food expenditures than for food expenditures, though this is partly reflects that fact that food expenditures are simply larger than non-food expenditures. Measured relative to total consumption, intra-annual food consumption variability is typically more important than non-food variation (with the possible exception of Uganda). Third, intra-annual variability in both food and non-food consumption is typically also of larger amplitude (but higher base levels too) for urban households, compared with their rural counterparts (the exception here being food consumption in Malawi). Fourth, for these three survey years, the observed intra-annual variability is lower in Malawi than in the other two countries (despite somewhat higher maize and rice price seasonality in the former). Surprisingly, food consumption is more variable in those Tanzanian regions with two harvests per year arising out of bimodal rainfall distributions.

[24] The results are based on estimations of equation (6) for each sub-region using survey design corrections and regional dummies. The results were robust to omitting either survey weights or regional indicators (correlations between the month effects across different specifications (with or without regional controls, with or without survey design strata and sampling weights) was 90 percent or higher. All regression results are available upon request.

A similar picture emerges when using the Gini coefficient as measure of intra-annual variability—higher intra-annual variability for non-food than food, higher for urban than rural, lower for Malawi than in the other two countries. In this context, the Gini coefficients have a direct interpretation in terms of storage. They imply that relatively modest food transfers from high to low consumption periods (of the order of 5% to 10% of food consumption levels) would be sufficient to eliminate seasonal variability in food consumption. Gini coefficients for non-food consumption are much higher, rising to 20%, but it is arguable that these may be of less concern since households may exhibit a much higher degree of intertemporal substitutability for non-foods. The picture is less consistent when using the (non-regression based) monthly averages as in Table 2, providing support to the use of the regression based approach described by equation (6).

Clearly, the estimated intra-annual variations are substantial, underscoring the challenge that households face in smoothing their food (and non-food) consumption. At the same time these intra-annual variations cannot be identified as regular seasonal deviations, given that they reflect the experience of a single year. This makes it impossible to distinguish between regular seasonality in food and non-food consumption and irregular or sampling variation specific to the survey year. With a second survey year available for Tanzania (2010-2011), a start can be made in gauging the annual specificity of the observed intra-annual variation in consumption (Table 7). There remains substantial intra-annual variation in both food and non-food consumption, with the latter being larger in relative terms than the former, across both years. Yet the geographical patterns have shifted, with intra-annual variation in food consumption especially pronounced in urban areas in 2008-9, while it is much more pronounced in the rural areas in 2010-11. When looking at the pooled sample, there remains substantial intra-annual variability, though the effects are no longer as pronounced as in either of the survey years. While this underscores the need for longer time series (or repeated cross-sections), which are rarely available in practice, to gauge seasonality in consumption as such, it does confirm the lack of intra-annual food consumption smoothing capacities of many households.

Several robustness checks and heterogeneity analyses on the intra-annual variability consumption indicators were performed.[25] First, we have examined intra-annual variation in food and non-food consumption by income and asset index quartile for each country, which indeed shows more seasonality for the non-poor and most intermediate income classes. Seasonality in consumption seems lower for poorer contexts, both across countries but also in relation to the rural-urban classification. It is possible that seasonal price impacts initially increase with income before eventually being declining for the wealthiest, suggesting a seasonal Kuznets effect. Second, we have looked whether the very large non-food intra-annual fluctuations in Uganda were driven by specific household categories within the sub-samples. Coffee is the main export crop in Uganda. Removing coffee growers from the Ugandan rural sub-samples tended to slightly increase the non-food consumption gap and decrease the food gap, but without making significant differences. Third, we have experimented with a number of alternative specifications adding additional control variables.[26] The resulting estimates of consumption variability appear very robust and the amplitude of this variability remains largely unaffected by augmented specifications.

Finally, the link between the estimated intra-annual fluctuations in food and non-food consumption for the year in question and the regular staple price seasonality observed over the longer sample is explored (Figure 6). The estimated month effects obtained at the sub-sample level for food and non-food expenditures are reweighted according to their shares in the national sample size to construct a "re-aggregated" national month effect. For presentational purposes, the intra-annual fluctuations are subsequently smoothed using a triangular 1:2:1 kernel centered on the reporting month (in effect generating a moving average of the estimated monthly factors with 0.25 weight applied to the preceding and subsequent month and 0.5 to the month concerned). They are each expressed as shares of total consumption change. To account for possible substitutability between staple foods, the seasonal factors of a staple foods price index are used, which is obtained

[25] Results are available from the authors upon request.
[26] The additional right-hand side variables comprised income, asset index, and household head employment status, as well as household size.

as the weighted average of the seasonal factors for the key staples considered weighted by the expenditure shares for those staples in the sub-sample under consideration, obtained by weighting the seasonal factors for each staple by its (annual) expenditure share..

Consumption closely tracks the seasonal movements of the staple price index in each of three countries. While there is some difference in the amplitude,[27] the regularity observed in the (inverse) joint movement in each of these three different settings, is striking. Household consumption (in real terms, i.e. in quantities) is lower when staple prices are higher, and higher, when staple prices are lower. Also, the subcomponents of consumption, food and non-food, move together, both declining when prices are higher, and increasing when staple prices are lower . Households smooth their food consumption partly by reducing (or postponing) their consumption of non-food items. The spikes in non-food consumption in March to May in Uganda, when staple prices are higher (and the subsequent overshooting downward in months July and August) are a notable exception.

Overall, the findings suggest that the intra-annual variability in household consumption may well follow from seasonality in food prices. That said, it cannot be excluded that third factors correlated to both price and consumption movements cause the observed similarity in price and consumption movements. A possible candidate might be a higher disease incidence during the rainy season (e.g. because of malaria)coinciding with the hunger season when food prices are high. However, no seasonal pattern was evident in self-reported disease incidence.

6 Conclusion

This study has revisited the evidence on food price seasonality and intra-annual variation in consumption in a wide variety of settings in three countries in eastern and southern Africa. Overall, the findings suggest that the current neglect of price seasonality and the inability of households to

[27] In Malawi, seasonality in food consumption exhibits a substantially lower amplitude than that in staple food prices while it is somewhat greater in Tanzania and of a comparable order of magnitude in Uganda (about 50% higher for both).

fully smooth their consumption within the year may be premature. Regular seasonality appears to contribute between 20% and 40% of overall food price volatility in the three countries examined, with wholesale maize prices during the peak months estimated to be 30 to 50 percent higher than those during the troughs. While some seasonality in food prices is natural given storage costs, the levels observed in the domestic countries of the study countries in this paper are two to three times higher than those in the international markets.

The empirical analysis further shows a strong negative association between price seasonality and intra-annual fluctuations in both food and non-food consumption. This indicates that a large proportion of African households has a limited ability to smooth consumption, and that there are good indications that such fluctuations may partly follow from an excessive seasonal behavior of staple prices.

There are multiple implications. First, significant welfare gains can be achieved by improving households' smoothing capacities. Second, the burgeoning literature on food price volatility, much of which focuses on financial and energy market influences on food prices, has largely neglected the more prosaic deterministic seasonal factors most immediately obvious throughout Africa. These could be reduced through more secure storage at village level, a reduction in transport costs, and increased intra-African food trade. Third, turning to methodology, poverty measurement is likely to be sensitive to seasonal issues. This should be taken into account in survey design since a sample which is nationally random may fail to be seasonally random. Overall, seasonality in prices and welfare remains much of an issue in East and Southern Africa and probably also throughout the remainder of the continent.

Many of our results on consumption are based on limited data and are suggestive rather than conclusive. Future work will bring in further survey waves but may also extend to a wider range of welfare indicators, including indicators of longer term impacts such as child growth and nutrition.

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Table 1: Description of the market price data by country

	Malawi	Tanzania	Uganda
Common staples	Maize, rice, millet/sorghum (exc. Malawi), beans, Cassava fresh		
Staples		Potatoes (irish)	Sweet and irish potatoes, matoke
Pulses and oilseeds	Groundnuts		Groundnuts
Vegetables and fruits	-	Onions, pineapples, bananas, oranges, tomatoes, carrots, cabbage	
Processed food		Wheat flour	
Time frame	2005-12	2000-2012	2000-2012 (2005-12 for retail markets)
Wholesale products	5	6	9
Retail products	-	12	14
# marketplaces	72	20	8
Total #markets	360	360	170

Table 2: Average food and non-food expenditures per interview month

	Malawi 2010-11		Tanzania 2008-09		Uganda 2009-10	
Means	Food	Non food	Food	Non food	Food	Non food
January	335	156	428	173	361	281
February	301	129	394	122	320	216
March	361	138	498	260	275	214
April	388	160	431	155	296	277
May	374	154	447	167	338	305
June	321	127	506	197	362	313
July	328	145	436	188	307	150
August	415	199	424	187	327	138
September	374	172	466	171	332	250
October	322	150	464	198	343	257
November	271	121	409	179	406	300
December	344	153	498	158	408	274
Gap	**42.6%**	**50.2%**	**24.9%**	**75.7%**	**39.6%**	**81.7%**
Annual average	344	150	450	180	339	248

Table 3: Food expenditure and cereal expenditure staple shares across countries, location and time

		Food home share of total cons	Staples share of food home cons	Rice share of staples cons	Maize share of staples cons	Sorghum &millet share of staples cons	Cook. bananas share of staples cons.	Cassava share of staples cons.
Malawi (%)	National average	**63.0**	**40.1**	**6.9**	**68.0**	**1.1**	**0.8**	**6.3**
	Rural average	64.8	41.2	5.5	71.7	1.3	0.9	6.7
	Urban average	53.7	34.1	14.3	48.6	0.2	0.3	4.2
	National minimum (month)	60.6	36.7	3.2	56.9			3.6
	National maximum (month)	66.1	45.1	9.7	81.1			8.4
	Gap (log)	**8.7**	**20.6**	**110.1**	**35.5**			**85.0**
Tanzania (%)	National average	**76.8**	**50.0**	**17.3**	**47.1**	**4.0**	**6.5**	**10.7**
	Rural average	80.0	52.0	13.3	50.6	4.3	6.9	12.5
	Urban average	65.6	43.1	31.1	35.0	2.9	4.9	4.4
	National minimum (month)	74.8	46.7	10.8	35.1		3.6	5.7
	National maximum (month)	80.4	55.2	22.2	65.0		20.2	17.6
	Gap (log)	**7.1**	**16.7**	**72.3**	**61.6**		**172.0**	**112.8**
Uganda (%)	National average	**54.3**	**50.3**	**5.6**	**19.5**	**5.8**	**22.6**	**22.2**
	Rural average	58.8	51.9	3.3	20.2	6.6	21.0	25.3
	Urban average	42.9	43.6	14.3	17.2	2.6	28.8	10.5
	National minimum (month)	49.6	43.9	3.8	13.5		17.8	13.4
	National maximum (month)	61.3	56.0	6.5	29.7		25.7	29.1
	Gap (log)	**21.2**	**24.5**	**54.2**	**79.2**		**36.8**	**77.3**

Note: Staple items comprise all cereals, tubers, and starchy products consumed crude or processed: wheat, rice, sorghum, millet, maize, cooking bananas, cassava, irish and sweet potatoes, yams. Pulses like beans or peas or oilseeds like groundnuts are not considered. The table only displays the shares of the top five staple commodities consumed across the three countries, which is why those shares do not sum up to one.

Table 4: Conditional and unconditional seasonality price gaps (%) and standard deviations averaged across markets per country

Commodity	Seas. Indicator	Malawi		Tanzania		Uganda	
		Average (%)	Within-country SD (%)	Average (%)	Within-country SD (%)	Average (%)	Within-country SD (%)
Maize wholesale	Conditional	54	10	31	10	33	10
	Uncond.	57	9	28	10	33	7
Maize retail	Conditional			27	11		
	Uncond.			25	11		
Rice wholesale	Conditional	22	10	21	5	17	7
	Uncond.	23	10	19	4	15	4
Rice retail	Conditional			15	5	15	7
	Uncond.			15	4	18	7
Millet wholesale	Conditional			20	8	25	8
	Uncond.			18	8	24	7
Sorghum wholesale	Conditional			22	7	25	5
	Uncond.			17	6	28	8
Matoke	Conditional					42	13
	Uncond.					45	12
Cassava fresh	Conditional	29	11	26	9	26	8
	Uncond.	33	11	31	9	25	10
Irish potatoes	Conditional			25	7	26	16
	Uncond.			29	9	24	9
Groundnuts	Conditional	36	14			22	6
	Uncond.	36	12			23	6
Beans wholesale	Conditional	33	12	23	6	29	4
	Uncond.	35	12	28	9	30	5
Beans retail	Conditional			14	5		
	Uncond.			16	6		
Onions	Conditional			44	11	36	7
	Uncond.			40	11	39	9
Tomatoes	Conditional			50	13	38	10
	Uncond.			46	12	37	10
Oranges	Conditional			45	9	46	20
	Uncond.			44	10	37	18
Pineapples	Conditional			40	18	38	16
	Uncond.			46	19	33	11
Flour	Conditional			6	2		
	Uncond.			11	2		

Table 5: ANOVA decomposition of (conditional) price seasonality gaps

Source of variance	Partial SS	DF	F stat		% explained
MODEL - ANOVA with 3-way interactions	21.612	889			
Crop / product	8.258	19	35.49	***	**38.2**
Market place and country	3.963	102	3.17	***	**18.3**
Crop / product x location	8.988	691	1.06	***	**41.6**
Market type	0.046	1	3.76	***	0.2
Market type x crop/product	0.093	6	1.27	**	0.4
Market type x location	0.085	23	0.30		0.4
Location x market type x crop/product	0.178	47	0.31		0.8
Total SS	21.612				

Table 6: Seasonality indicators of food and non food consumption by country and sub-sample

		MALAWI 2010-11				TANZANIA 2008-09			UGANDA 2009-10		
		Food									
		Urban	Rural north	Rural central	Rural south	Urban sub sample	Rural with 2 harvests	Rural with 1 harvest	Urban sub sample	Rural with 2 harvests	Rural with 1 harvest
Gap (%)	Estimated[1)]	28	59	43	31	82	35	26	75	46	49
	Sample average	44	64	49	32	76	55	23	55	56	67
Gini	Estimated[1)]	0.04	0.08	0.06	0.05	0.11	0.05	0.04	0.09	0.06	0.06
	Sample average	0.06	0.09	0.06	0.05	0.08	0.08	0.04	0.08	0.08	0.09
Joint significance wald test of the seasonal dummies		1.15	6.95***	5.06***	6.58***	4.37***	1.29	1.07	3.16***	4.64***	2.04**
R^2 of the regression		0.285	0.112	0.12	0.11	0.305	0.228	0.106	0.153	0.209	0.258
		Non food[2)]									
Gap (%)	Estimated[1)]	76	36	24	21	107	86	82	233	91	90
	Sample average	57	76	38	32	123	49	100	237	69	103
Gini	Estimated[1)]	0.08	0.09	0.05	0.04	0.17	0.15	0.1	0.2	0.11	0.12
	Sample average	0.07	0.09	0.06	0.05	0.16	0.08	0.1	0.21	0.1	0.17
Joint significance wald test of the seasonal dummies		1.61*	5.24***	2.97***	4.95***	6.61***	2.17**	2.79***	12.75***	4.47***	2.61***
R^2 of the regression		0.386	0.152	0.156	0.205	0.452	0.175	0.157	0.496	0.242	0.282

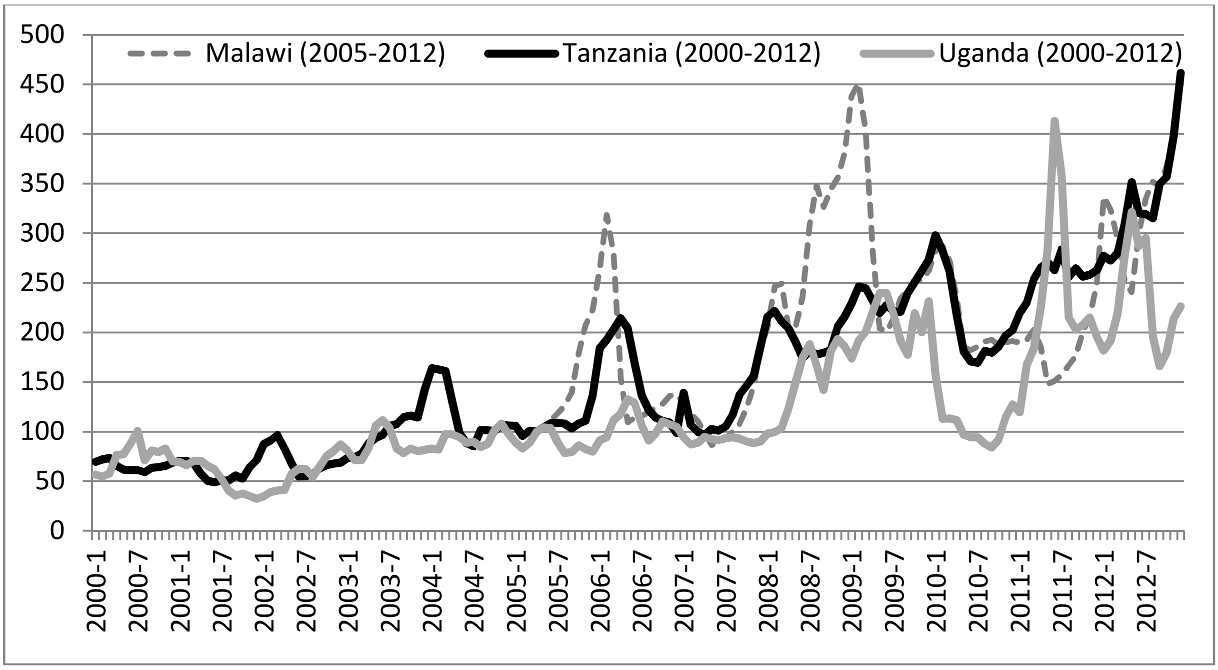
Note: [1)] The estimated indicators are those obtained from the seasonal factors estimated with a regression on basic non-seasonal correlates (household head education, sex, and age, AEZ, a control for the agricultural year, and controls for rural/urban and administrative region) accounting for sampling household weights, [2)]Education expenses are removed from the non-food aggregate. *, **, *** denote statistical significance at the 10%, 5% and 1% level respectively.

Table 7: Seasonality indicators of food and non food consumption by sub-sample and survey wave in Tanzania

		Survey 1: 2008-09			Survey 2: 2010-11			Pooled sample		
		Food								
		Urban sub sample	Rural with 2 harvests	Rural with 1 harvest	Urban sub sample	Rural with 2 harvests	Rural with 1 harvest	Urban sub sample	Rural with 2 harvests	Rural with 1 harvest
Gap (%)	Estimated[1)]	82	35	26	27	58	40	27	59	32
	Sample average	76	55	23	49	38	50	45	36	35
Gini	Estimated	0.11	0.05	0.04	0.05	0.08	0.05	0.04	0.06	0.04
	Sample[1)] average	0.08	0.08	0.04	0.06	0.06	0.06	0.06	0.05	0.03
Joint significance wald test of the seasonal dummies		4.37***	1.29	1.07	1.45	3.25***	1.64*	1.59*	2.85***	1.12
R^2 of the regression		0.305	0.228	0.106	0.291	0.255	0.149	0.277	0.226	0.116
		Non food[2)]								
Gap (%)	Estimated[1)]	107	86	82	82	108	51	55	91	66
	Sample average	123	49	100	113	52	53	104	42	63
Gini	Estimated[1)]	0.17	0.15	0.10	0.09	0.12	0.09	0.08	0.09	0.08
	Sample average	0.16	0.08	0.10	0.16	0.08	0.08	0.14	0.07	0.06
Joint significance wald test of the seasonal dummies		6.61***	2.17**	2.79***	1.4	2.99***	3.41***	2.29***	2.98***	2.41***
R^2 of the regression		0.452	0.175	0.157	0.377	0.238	0.193	0.372	0.187	0.162

Note: [1)]The estimated indicators are those obtained from the seasonal factors estimated with a regression on basic non-seasonal correlates (household head education, sex, and age, AEZ, and regional controls) accounting for sampling household weights, [2)]Education expenses are removed from the non-food aggregate as they introduce recall bias. *, **, *** denote statistical significance at the 10%, 5% and 1% level respectively.

Figure 1: Evolution of monthly national median wholesale maize price (Jan 2000-Dec 2012)



Note: Prices in nominal terms. April 2005=100

Figure2: Comparison of national maize wholesale conditional seasonal price factors with SAFEX benchmark

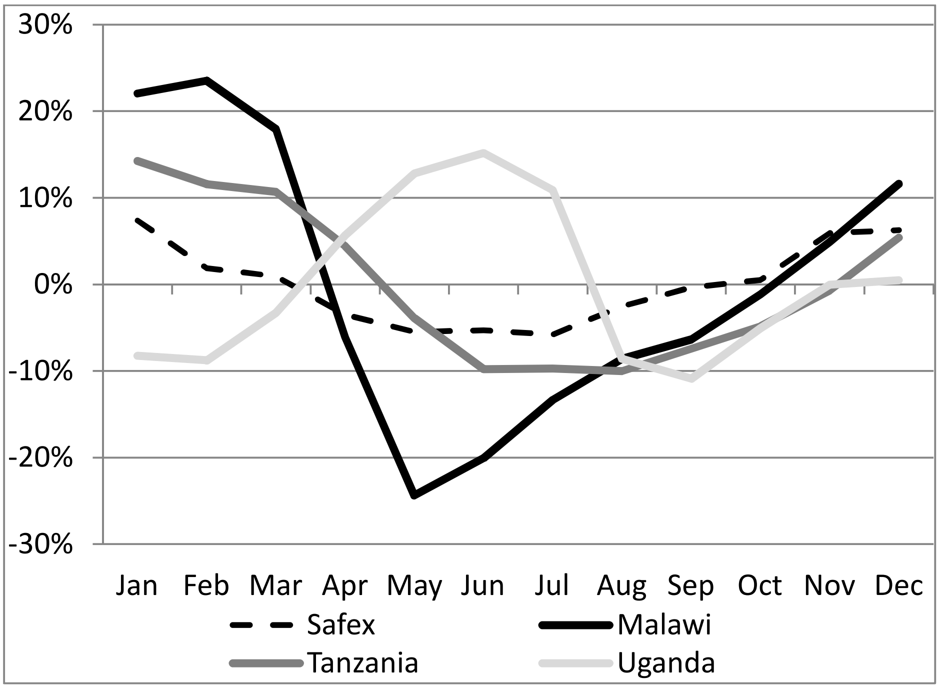


Figure 3: Comparison of the national rice wholesale conditional seasonal price factors with the Bangkok rice export market benchmark

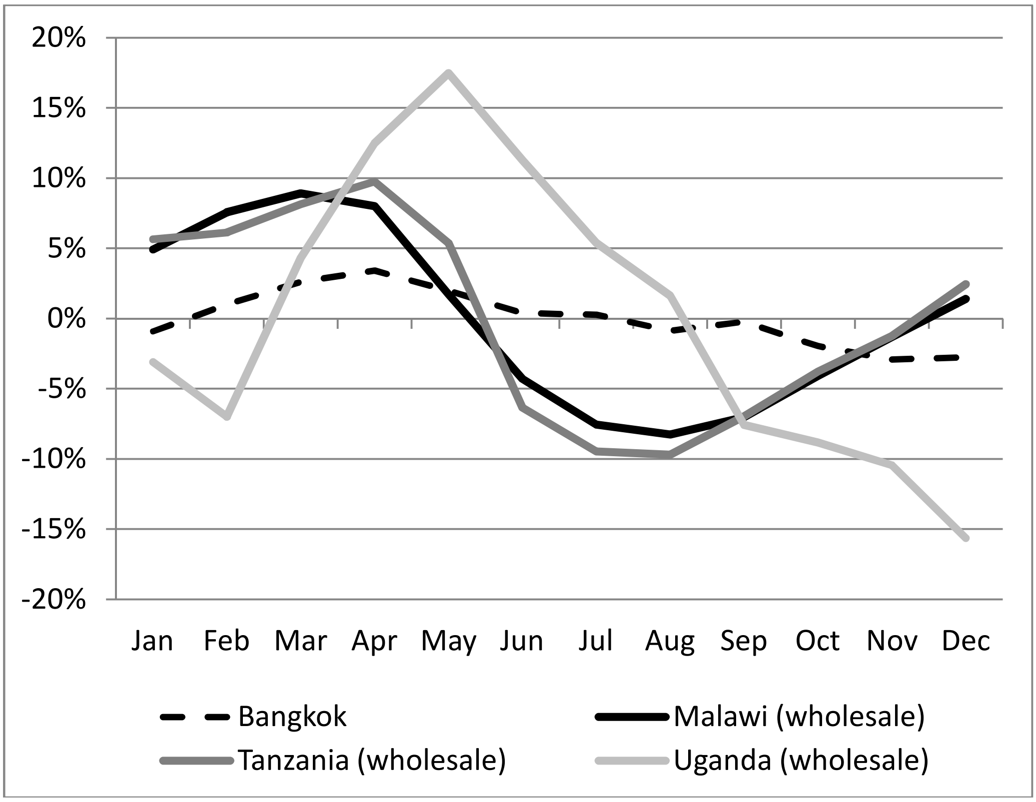
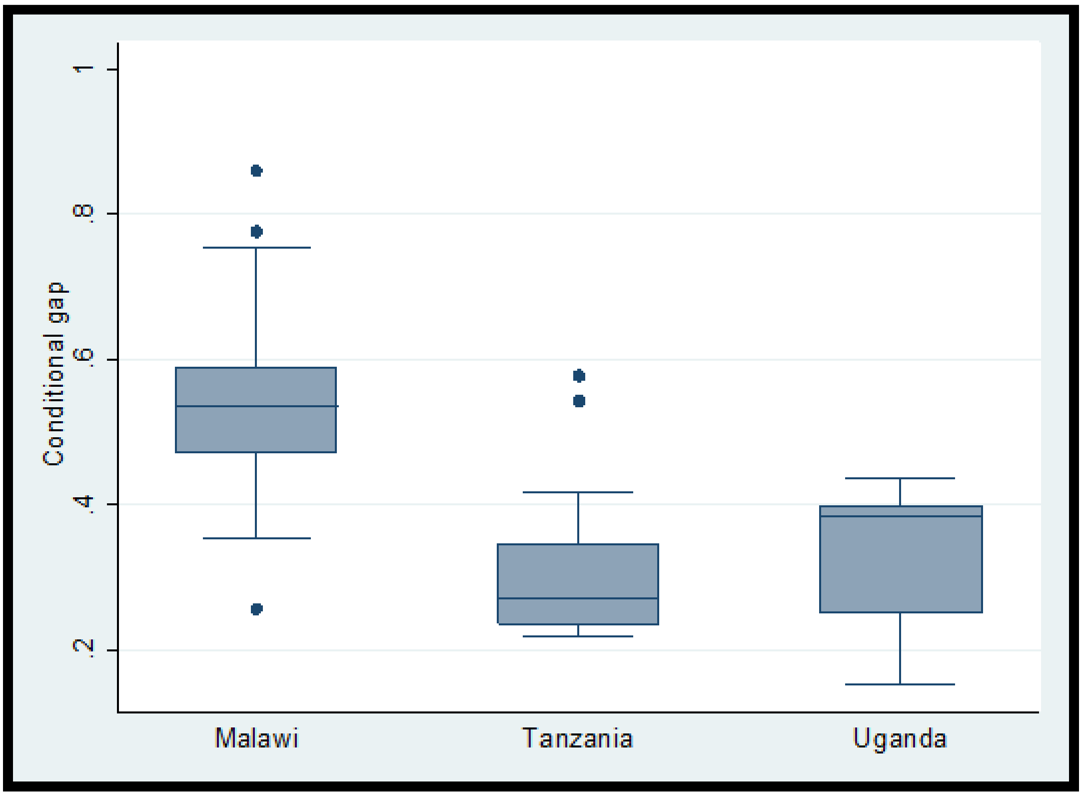
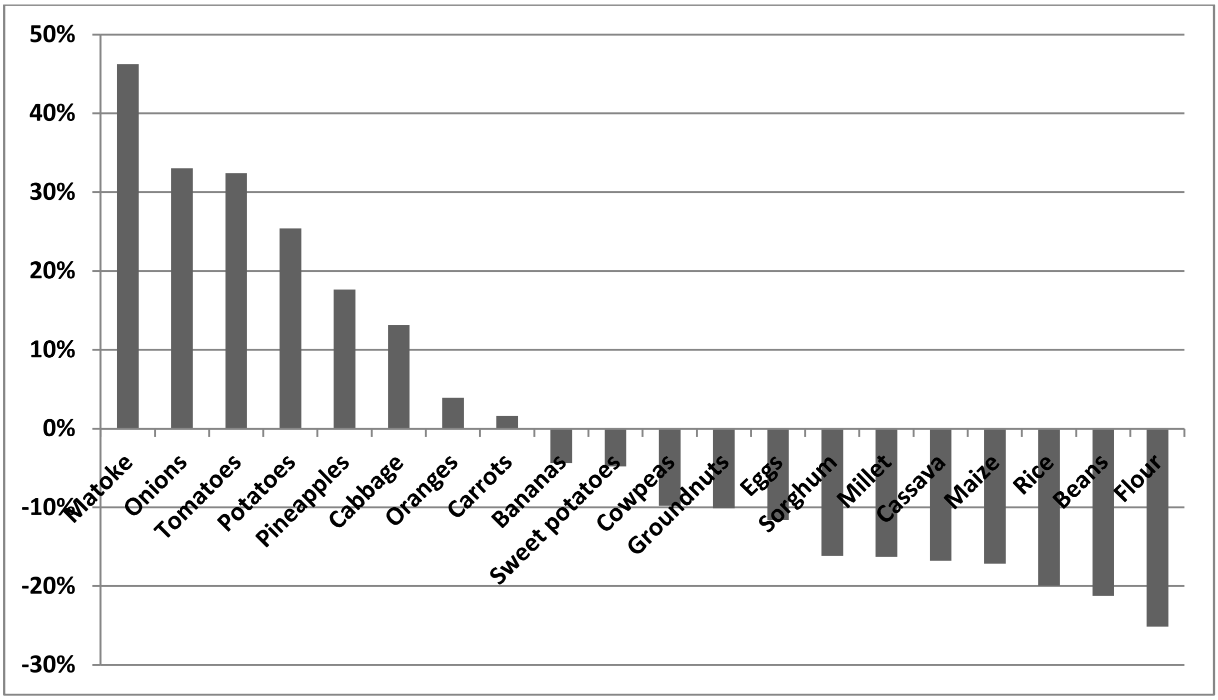


Figure 4: Distribution of seasonal wholesale maize price gaps across markets



Note: The Box plots represent distributional statistics of the conditional gaps by country for wholesale maize prices. The lower and upper horizontal lines represent the minimum and maximum values (excluding outliers) respectively while the 25 and 75% percentile values are represented by the bottom and top bars of the box (which represents the inter-quartile). The line in the box represents the median value across market locations. The dots outside the bars are outliers (1.5 times more/less than the upper/lower quartile.

Figure 5: Pure product effects on seasonal price gaps (conditional)



Note: Those figures are derived from the ANOVA OLS regression coefficients of the pure products effects once controlling for other sources of heterogeneity in the conditional price gaps and interaction with the product effects. Estimated coefficients are recentered so as to locate the seasonality premium of all products with respect to an “average” product.

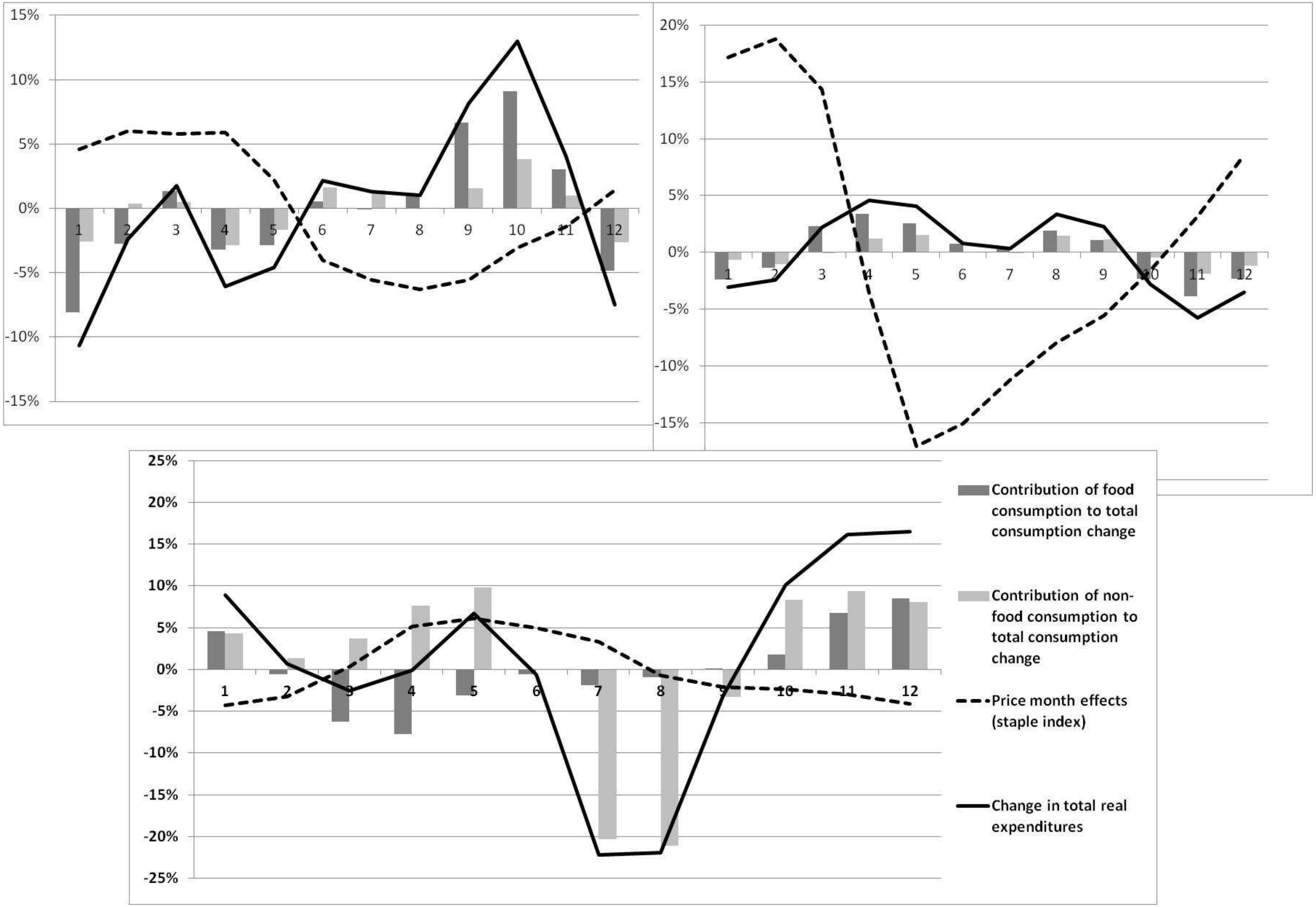


Figure 6: Re-weighted national estimated consumption cycles (smoothed) against weighted conditional staple price cycles – a) Tanzania (top left), b/ Malawi (top right), c) Uganda (bottom)

APPENDIX

Table A1- Descriptive statistics on correlates of consumption and interview month

		Malawi 2010-11		Uganda 2009-10		Tanzania 2008-09	
		Weighted mean	SD	Weighted mean	SD	Weighted mean	SD
Male headed hh		80.39%		75.73%		79.54%	
Age of the hh head		42.429	14.61	45.113	14.756	46.821	14.64
Education of the hh head							
Primary incomplete		51.06%		36.60%		20.79%	
Primary completed		7.08%		12.94%		46.92%	
Secondary incomplete		10.86%		15.39%		7.29%	
Secondary complete		6.48%		10.41%		1.10%	
Post secondary technical		1.15%				0.02%	
University		1.28%				0.48%	
Adult literacy program						0.95%	
Illiterate		**22.09%**		**24.65%**		**22.45%**	
HH size		5.635	2.266	6.837	3.499	6.616	3.715
Active hh head		92.40%				99.91%	
Dependency ratio				53.15%			
Urban hh		15.52%		21.18%			
Interview month:	1	9.30%		6.57%		9.64%	
	2	6.55%		8.57%		9.31%	
	3	11.84%		8.69%		3.97%	
	4	6.93%		9.58%		2.51%	
	5	7.48%		7.91%		8.89%	
	6	6.34%		9.84%		7.44%	
	7	10.14%		9.28%		9.39%	
	8	5.48%		9.79%		10.59%	
	9	9.30%		6.65%		10.56%	
	10	9.54%		8.12%		10.11%	
	11	10.83%		8.26%		8.96%	
	12	6.26%		6.74%		8.62%	
New or former ag. Season		16.10%				18.08%	

Table A2: Trend specification of price time series models

	Estimated price trend					
	Wholesale (% of marketplaces)					
	Malawi		Tanzania		Uganda	
	Deterministic	Constant drift	Deterministic	Constant drift	Deterministic	Constant drift
Maize	3	82	10	85	13	75
Rice	4	50	10	60	0	38
Millet			5	85	13	100
Sorghum			10	95	0	57
Cassava	10	83				50
Potatoes (Irish)			25	95	88	0
Potatoes (Sweet)					0	100
Groundnuts	7	78			0	75
Beans	7	85	15	100	13	88
	Retail (% of marketplaces)					
	Malawi		Tanzania		Uganda	
	Deterministic	Constant drift	Deterministic	Constant drift	Deterministic	Constant drift
Maize			16	100		
Rice			0	75	0	13
Matoke					0	71
Cassava			10	95	0	13
Potatoes (Irish)					50	88
Potatoes (Sweet)					0	25
Beans			15	85		
Cabbage			30	85	50	100
Carrots			20	80	38	100
Onions			30	100	75	100
Tomatoes			25	100	50	100
Bananas			20	90	0	100
Oranges			20	100	63	100
Pineapples			40	95	25	88
Flour			0	90		

Table A3: Significance and features of seasonal factors in the price time series models

	Seasonality								
	Wholesale (% of marketplaces)								
	Malawi			Tanzania			Uganda		
		Significant at			Significant at			Significant at	
	Variable	5%	1%	Variable	5%	1%	Variable	5%	1%
Maize	35	97	94	5	90	85	50	100	50
Rice	42	54	42	30	95	95	50	75	50
Millet				25	30	20	50	75	50
Sorghum				45	5	5	29	43	43
Cassava	35	14	6				17	67	67
Potatoes (Irish)				35	70	50	63	50	0
Potatoes (Sweet)							50	67	67
Groundnuts	56	53	42				13	100	75
Beans	44	64	46	30	85	60	38	100	100
	Retail (% of marketplaces)								
	Malawi			Tanzania			Uganda		
		Significant at			Significant at			Significant at	
	Variable	5%	1%	Variable	5%	1%	Variable	5%	1%
Maize				0	47	32			
Rice				40	75	75	38	63	63
Matoke							29	100	100
Cassava				30	20	5	38	38	13
Potatoes (Irish)							13	88	75
Potatoes (Sweet)							75	75	50
Beans				15	40	30			
Cabbage				40	30	15	25	63	38
Carrots				30	15	5	38	50	25
Onions				15	65	50	13	63	50
Tomatoes				25	70	45	13	63	50
Bananas				25	30	5	63	0	0
Oranges				10	65	45	25	75	75
Pineapples				40	50	40	75	50	50
Flour				55	0	0			