International interdependence between cash crop and staple food futures price indices: A wavelet-BEKK-GARCH assessment

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Abstract:

This study examines the price level and volatility interaction between international staple food and cash crop futures price indices. Understanding the relationship between these commodities bears significant implication for net food importing developing countries that depend on cash crop to finance food import bills. We use a wavelet analysis to decompose and denoise the price indices and then apply a BEKK-MGARCH approach to analyze the relationship across time-frequency domains. Results indicate the level of correlation and volatility linkages are strongest at lower frequencies (i.e. longer run), with markets adjusting quickly to volatility shocks after a high initial impact.

Acknowledegment:

JEL Codes: G13, C32

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Keywords: Volatility spillover, wavelet, MGARCH, cash crops, staple food crops
JEL classification: Q11, Q13, G13, C32

1 Introduction

A large number of developing countries still rely for the bulk of their export earnings on the production and export of cash crops. In 2013, for instance, export of tropical beverage crops, fruits, and sugar as a percentage of total agricultural products was estimated at 77 percent, 74 percent, and 71 percent for Burundi, Mauritius, and Swaziland, respectively. Also in that year, these products accounted for 43 percent, 27 percent, and 24 percent of total merchandise export for Burundi, Uganda, and Kenya, respectively (FAO, 2016). At the same time, many of these countries are net food importers and depend on international markets to meet established national food security requirements. Therefore, export earnings generated by cash crop trade could contribute to sustaining food imports, as these shipments need to be financed in foreign currencies. While a number of studies have looked at the price relationship at the farm and national levels, very few have carried out the analysis from an international level perspective.

In this paper, we explore the price relationship between international cash crop and staple foods by examining their co-movement and dynamics in terms of price level and volatility. While movements in quantities together with prices determine the direction and magnitude of export earnings, the focus in this paper is exclusively on the price component of the equation given its relative importance. Previous research shows that international demand for agricultural commodities (including cash crops) is generally inelastic, meaning that movements in prices outweigh those of quantities (FAO, 2004).

To gain insights into the staples-cash price relationship, we apply a wavelet analysis to decompose the series into three time scale levels corresponding to short, medium, and long run. With a wavelet approach, periods of high volatility interactions are brought out clearly at different scales (Percival et al., 2004). A multivariate Baba, Engle, Kraft and Kroner (BEKK)-Generalized Autoregressive Conditional Heteroskedasticity (GARCH) framework (Engle and Kroner, 1995) is then applied to each of the three frequency levels to explore the dynamics of the volatility interaction at various time horizons. To minimize the effect of model convergence issues that are often associated with BEKK-GARCH parameterization, we construct two price indices that we use for the estimation exercise. The first price index captures daily futures price changes for sugar, cotton, cocoa, and coffee and is referred to as the cash crop price index. The second index depicts daily futures price changes for wheat, maize, and soybeans, and represent the staple food crop price index. Both price indices are volume weighted, with data on daily volumes obtained from the futures markets where the commodity is traded[1]. An impulse response analysis on the estimated conditional variances is then carried out to provide further evidence of the volatility dynamics and transmission across cash and staple food markets. These responses include both the direct effect estimated through the estimated conditional variances and the indirect effects through the conditional co-variances.

Our research contributes to the literature in three aspects. First, as opposed to the bulk of the existing studies on the relationship between staple foods and cash crops, we examine the price level and volatility interaction from a global perspective. Hence, we contribute to providing evidence-based analysis on the potential contribution of cash crop earnings to food import bills, particularly during periods of high and volatile food prices. Second, with the objective of gaining additional insights, we use wavelet transform to decompose the price series into different time scales. This way, we are able to reveal aspects of volatility dynamics otherwise hidden in the original series and account for asymmetries due to time scales. Finally, we measure the persistence of volatility shocks in the cash and staples markets by estimating impulse response functions on the estimated conditional variances.

The rest of the paper is organized as follows: the next section covers a short review of relevant studies on cash crops and staples and the use of the GARCH methodology. We then present a discussion on the methodology and data used in the analysis, followed by a discussion about the main empirical results and observations. Finally, a summary of the main conclusions and implications are provided in the last section.

[1] Sugar, cotton, cocoa, and coffee daily futures prices and volumes are taken from the ICE, New York, while those for wheat, maize, and soybeans are taken from the CBOT, Chicago.

2 Literature review

The literature on the relationship between international staple food and cash crop prices is mostly concerned with farm resource allocation, and precisely whether cash crop production and export compete for resources with food crop production. The concern is that a focus on cash crop production may create some risks for rural smallholder farm households notably in terms of food security. One school of thought argues that cash crop production is detrimental to food security (Maxwell and Fernando, 1989; Mittal, 2009), while others argue that a cash crop strategy improves farm welfare because proceeds from cash crop provide the means to buy food in the local market (i.e. the access dimension of food security) (Timmer, 1997; Von Braun and Kennedy, 1986; Weber et al., 1988). Recent papers in this field argue that staple food and cash crops should be viewed as complementary rather than competitive. By participating in cash crop schemes, smallholders can have access to productivity enhancing inputs such as credits, management training, fertilizers, and other factor inputs which would not have been available without the participation in cash crop programs (Govereh and Jayne, 2003; Theriault and Tschirley, 2014).

While many studies provide some interesting insights into the mechanism that explain the allocation of farm resources to the production of cash crops by smallholders in developing countries (Norton and Hazell, 1986), they seldom shed some light on the interaction of cash and staple food prices at the international market level. The dynamics at the international level is relevant because it often determines movements in domestic prices. For example, coffee prices received by farmers in Ghana are associated with futures prices negotiated at the Intercontinental Exchange (ICE) market in New York. Similarly, wheat imports prices paid by Egypt, the world's largest wheat importer, are linked with wheat futures prices such as those negotiated at the Chicago Board of trade (CBOT) or EURONEXT/MATIF in Paris (Janzen and Adjemian, 2017). Hence, the benefit of specializing in cash crop production and the use of revenues to import food hinges on the interaction of cash crop and staple food futures prices. High exports revenues can help alleviate partially, or fully, the burden associated with food import bills during periods of high international food prices. The extent of the contribution depends on several factors which include, the contribution of cash crop earnings to total export revenues, the price elasticities of the international demand and supply for cash crops, and currency movements.

Whereas the available research into the volatility dynamics between cash crop and staple food international prices is relatively limited, studies using GARCH methodology to assess the interdependence among markets, including agriculture, are quite prolific. For example, Vivian and Wohar (2012) used a GARCH approach to examine the volatility interaction among a sample of 28 commodities and found significant volatility linkages and volatility persistence even after taking structural breaks into account. Using a BEKK and a dynamic conditional correlation (DCC) trivariate GARCH approach, Gardebroek and Hernandez (2013) found evidence of a unidirectional volatility spillover running from maize to ethanol, but weak evidence of transmission from crude oil to maize market in the United States. A multivariate GARCH with structural breaks is applied by Teterin et al. (2016) to explore the volatility dynamics between crude oil and maize future prices. Their results show that the volatility between crude oil and maize is less persistent when accounting for structural breaks in the mean and volatility. In a recent study, Al-Maadid et al. (2017) conclude that there is significant volatility spillover effects between energy and food markets, with the interaction greater during the 2006 food crisis and the 2008 financial crisis. Other studies using a GARCH method to examine price volatility among commodities include Chang and Su (2010), Ji and Fan (2012), Harri and Hudson (2009), Nicola et al. (2016), and Trujillo-Barrera et al. (2012).

A growing number of studies looking at agricultural price volatility have recently been using wavelet-based techniques. While these techniques are common in the fields of physics, medicine, and mathematics, it is only recently when their application to economics and finance has been expanding. The advantage of this approach is that it allows a decomposition of the main components of a price series to obtain additional insights into the underlying factors shaping price movements (Percival et al., 2004). Studies using wavelets include Filip et al. (2016), Kristoufek et al. (2016), Mensi et al. (2017), Ftiti et al. (2016), Power and Turvey (2010), and Pal and Mitra (2017). Wavelets analysis is also often used to denoise price series to better capture the fundamental relationship underlying price volatility as in Jammazi et al. (2015) and Jammazi and Aloui (2012).

The use of GARCH-based techniques to investigate the interaction between the financial market and commodities, including agriculture, is also prolific. For exemple, Mensi et al. (2013) assessed the volatility integration between energy, food, gold, and beverages price indices, and the United States' S&P 500 index. Their results show significant return and volatility transmission across markets. Gao and Liu (2014) used a bivariate GARCH model to investigate the volatility interdependence between the S&P 500 index and a sample of commodities, while Nazlioglu et al. (2013) looked at the volatility transmission between crude oil and agricultural commodity markets, evidencing significant mean return and volatility integration. Other papers examining the linkages between the financial markets and commodities include Olson et al. (2014), Park and Ratti (2008), Awartani and Maghyereh (2013), El Hedi Arouri et al. (2011), Malik and Ewing (2009), Diebold and Yilmaz (2012), and Grosche and Heckelei (2016).

3 Methodology and data

3.1 Wavelet

The wavelet transform is based on the mathematical operation of convolution, which specifies that the integral of the product of two functions, one of which is reversed and shifted, produces a third function which has similar features with the shifted and reversed function

(Torrence and Compo, 1998). The wavelet transform is based on two specific functions: 1) the father wavelet $\Phi(\mathrm{t})$, and 2) the mother wavelet $\Psi(t)$. A series of wavelets called daughter wavelets $\Psi_{u,s}(t)$ can then be built by simply scaling and translating (shifting) $\Psi(t)$:

$$\Psi_{u,s}(t) = \frac{1}{\sqrt{s}}\Psi(\frac{t-u}{s}) \tag{1}$$

where $\frac{1}{\sqrt{s}}$ is a normalization factor ensuring unit variance of the wavelet, i.e. $||\Psi_{u,s}(t)||^2 = 1$, and u and s are the location and scaling parameters, respectively (Crowley, 2005). The scaling parameter controls for the length of the wavelet and is related to the frequency of the input signal such that a larger (lower) value implies the wavelet will correlate with the low (high) frequencies contained in the time series. The term u determines the location of the wavelet in the time domain. A number of wavelets have been developed to capture specific frequency characteristics of time series, and these include the Daubechies, Haar, Morlet, and Mexican hat. There are two types of wavelet transform that are widely used in the literature: 1) the discrete wavelet transform (DWT) and 2) the continuous wavelet transform (CWT) (Crowley, 2005). The DWT is suitable for data compression and noise reduction, while the CWT is useful for smooth extraction of frequencies. Mother wavelets have to satisfy two main conditions: 1) zero mean, that is $\int_{-\infty}^{\infty}\Psi(t)dt = 0$, and 2) unit energy (localized in time or space), i.e.$\int_{-\infty}^{\infty}\Psi^2(t)dt = 1$. In addition, wavelets have to satisfy the admissibility condition, which guarantees a reconstruction of the original time series from its wavelet transform using the inverse transform (Shalini and Prasanna, 2016). For this paper, we use the DWT given the flexibility it offers in denoising time series (Crowley, 2005). Based on the DWT, any time series can be described as a linear combination of father and mother wavelets (Mensi et al., 2017):

$$\mathrm{X}(t) = \sum_k s_{j,k}\Phi_{j,k}(t) + \sum_k d_{j,k}\Psi_{j,k}(t) + \cdots + \sum_k d_{1,k}\Psi_{1,k}(t) \tag{2}$$

where j represents the multiresolution, or scale level, and k depicts the number of coefficient in each scale level. Further $s_{j,k}$ and $d_{j,k}$ are the scaling (or smooth) and detail (or wavelet) coefficients, respectively, and can be expressed as:

$$s_{j,k} = \int X(t)\Phi_{j,k}(t)dt \tag{3}$$

$$d_{j,k} = \int X(t)\Psi_{j,k}(t)dt \qquad \text{for j=1,2,…,j} \tag{4}$$

The detail coefficient $d_{j,k}$ captures the high frequencies contained in the input signal, or time series, while the scale coefficient $s_{j,k}$ captures the smooth part, or the long term trend, of the input function (Moya-Martínez et al., 2015). The original input function X(t) can be reconstructed as a linear combination of the calculated coefficients (Mensi et al., 2017):

$$\mathrm{X}(t) = S_j(t) + D_j(t) + D_{j-1}(t) + \cdots + D_1(t) \quad (5)$$

with the smooth, or approximation, components of the time series represented by $S_j = \sum_k s_{j,k}\Phi_{j,k}(t)$ and the details components of the series specified as $D_j = \sum_k d_{j,k}\Psi_{j,k}(t)$. In practice, a wavelet with some desired properties is chosen and convoluted with a time series to extract the various frequencies that are contained in the series. It is then possible to rebuild the series by excluding, for example, certain frequencies. The reconstruction of a time series using the DWT approach most often relies on Mallat's pyramid algorithm (Mallat, 1989), which consists of applying a series of low-pass and high-pass filters. Explicitly, a time series X(t) is convolved with high-pass and low-pass filters to extract the detail $\mathrm{D}_1(\mathrm{t})$ and approximation $\mathrm{S}_1(\mathrm{t})$ components of the series. Then $\mathrm{S}_1(\mathrm{t})$ becomes the input for the subsequent iteration phase to derive $\mathrm{D}_2(\mathrm{t})$ and $\mathrm{S}_2(\mathrm{t})$. This iterative process is repeated until the desired decomposition level j is achieved (Crowley, 2005).

In this paper, we use the Daubechies' "extremal phase wavelets" (Daubechies, 1992) and implement the DWT to denoise the cash and staple food index series. Typically, denoising the price indices implies removing those wavelet coefficients which do not contribute significantly to the signal. In terms of our index series, noise may represent short-term speculative behavior, scalping, herd behavior, outliers, or irrational price movements (Gardebroek and Hernandez, 2013). Daily observations such as futures prices typical contain a lot of noise which do not necessarily contribute to the underlying movement in prices.

3.2 GARCH approach

As highlighted in the literature review, the multivariate GARCH model has a wide application in the analysis of integration between markets. In this paper, we study the volatility spillover between cash crop futures price index and staple food futures price index at an international level. The basis for constructing the indices is discussed later in the data section. Our approach assumes that the variance-covariance matrix follows a BEKK-GARCH specification. The bivariate bivariate BEKK-GARCH model is expressed as follow:

$$A(L)r_t = \varepsilon_t \ , \quad (6)$$

and

$$\varepsilon_t | \omega_{t-1} \sim N(0, H_t)$$

where $A(L)$ is a 2 x 2 matrix polynomial in the lag operator L, r_t is a 2 x 1 daily return vector at time t, and ε_t is a 2 x 1vector of random errors representing the shocks, or innovations, at time t. H_t is a 2 x 2 conditional variance-covariance matrix, given market information ω_{t-1} available at time t-1. Equation (1) represents the mean conditional equation and describes the impact of own and lagged shocks as well as lagged innovations in other markets on the mean of a variable at time t. The order of the system can be selected on the basis of a standard information criterion (e.g. Akaike information criterion (AIC), the Schwarz information criterion (SIC)).

With respect to the form that H_t can take, it generally depends on the number of variables and the objective of the research. Given the objective of this study, we select the full BEKK-GARCH model, as it enables the measurement of cross-market ARCH and GARCH effects and own market effects. We use indices that capture cash crop futures price returns and staple futures price returns to ease model convergence and analysis. Also, the BEKK-GARCH ensures that H_t is a positive definite matrix. Based on the model proposed by Engle and Kroner (1995), the conditional variance-covariance matrix can be expressed as:

$$H_t = C_0^{'} C_0 + A_{11}^{'} \varepsilon_{t-1} \varepsilon_{t-1}^{'} A_{11} + G_{11}^{'} H_{t-1} G_{11} \tag{7}$$

Equation (7) can be expressed in matrix form:

$$H_t = C_0^{'} C_0 + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}^{'} \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1,}\varepsilon_{2,t-1} \\ \varepsilon_{1,t-1,}\varepsilon_{2,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}^{'} H_{t-1} \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix} \tag{8}$$

Where $C_0^{'} C_0$ represent the decomposition of the intercept matrix, with C_0 restricted to be a lower triangular matrix. The unrestricted n x n matrices A and G contain the own ARCH and cross-market ARCH effects and the own GARCH and cross-market GARCH effects, respectively. With this specification, it is possible to trace the effect of innovations and volatility in one market and how they transmit to other markets. These estimates are contained in matrices A and G. Expanding equation (8) yields the variance-covariance equations:

$$h_{11,t} = c_{11}^2 + a_{11}^2 \varepsilon_{1,t-1}^2 + 2a_{11}a_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}^2 \varepsilon_{2,t-1}^2 + g_{11}^2 h_{11,t-1} + 2g_{11}g_{21}h_{12,t-1} + g_{21}^2 h_{22,t-1} \tag{9}$$

$$h_{12,t} = c_{11}c_{21} + a_{11}a_{12}\varepsilon_{1,t-1}^2 + (a_{21}a_{12} + a_{11}a_{22})\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}a_{22}\varepsilon_{2,t-1}^2 + g_{11}g_{12}h_{11,t-1} + (g_{21}g_{12} + g_{11}g_{22})h_{12,t-1} + g_{21}g_{22}h_{22,t-1} \tag{10}$$

$$h_{22,t} = c_{21}^2 + c_{22}^2 + a_{12}^2 \varepsilon_{1,t-1}^2 + 2a_{12}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{22}^2 \varepsilon_{2,t-1}^2 + g_{12}^2 h_{11,t-1} + 2g_{12}g_{22}h_{12,t-1} + g_{22}^2 h_{22,t-1} \tag{11}$$

With the assumption that error terms follow a multivariate standard normal distribution, the BEKK-GARCH models are estimated by maximizing the log likelihood function using the

Berndt, Hall, Hall and Hausman (BHHH) algorithm. The conditional log likelihood function L for a sample of T observations is:

$$L(\theta) = \sum_{t=1}^{T} l_t(\theta), \text{ with}$$
$$l(\theta) = -log2\pi - \frac{1}{2}\log|H_t(\theta)| - \frac{1}{2}\varepsilon_t^{'}(\theta)H_t^{-1}(\theta)\varepsilon_t(\theta)$$

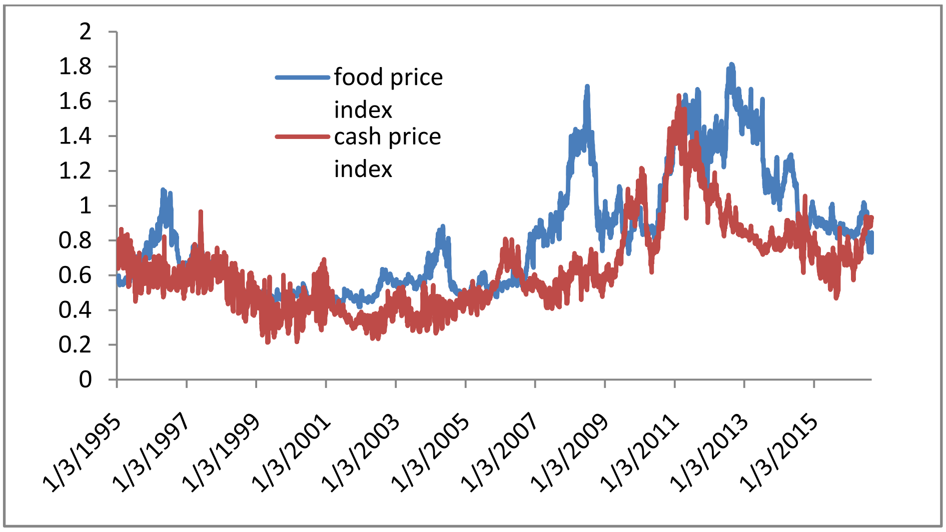
Where θ represents the vector of all the parameters to be estimated.

3.2 Data

For the purpose of easing model convergence and analysis, we develop two indices that capture movements in cash crop and staple futures prices. The cash crop futures index is constructed by taking the weighted average of the daily closing futures prices realized at the Intercontinental Exchange (ICE) for sugar No. 11 (SB) futures, cocoa (CC) futures, coffee "C" (KC) futures, and cotton No.2 (CT) futures. We first normalize the prices and use the daily traded volumes as weights to derive the daily futures price index. We follow a similar procedure for the staple food futures prices, where we use the daily closing futures prices realized at the Chicago Board of Trade (CBOT) for corn (C1) futures, soybeans (SB1) futures and wheat (W1) futures, and use the respective traded volumes as weights. For both indices daily futures prices and volume data are sourced from Bloomberg and cover the period of 3 January 1990 to 30 August 2016. As with similar studies, the analysis is undertaken using the returns of the index series by taking the differences in the logarithm of two consecutive price indices. Series expressed in returns are often stationary.

Figure 1 shows the daily price movements of both cash and staple food price indices. The graph highlights the extent of the volatility that underpins both markets. Overall, international cash and staple food prices display a gradual increase starting in 2002, with marked price spikes for the food index in 2008, 2011, and 2012. On the other hand, the cash price index peaks in 2011, driven by higher quotations for cotton, sugar, and coffee, but declines steadily afterwards to remain relatively firm between 2013 and 2016. The 2011 and 2012 spikes in the food price index reflect supply shocks in the cereal markets, while the 2008 sharp increase in the index is largely attributed to higher crude oil quotations which impacted the staple food market (Rosegrant et al., 2008). The sharp fall in the food index in mid-2008 follows the aftermath of the financial crisis characterized by a reduction in global aggregate demand. After a recovery in 2011 and 2012, the food price index falls gradually in mid-2012 to reach its pre-food crisis level (2007-2008).

Figure 1: Daily price index movements of selected cash and staple food commodities (2010 = 1)



4 Descriptive statistics and results

4.1 Descriptive statistics

The descriptive statistics of the price index return series are reported in table 1. The statistics show that the food price index has the largest daily return and the lowest standard deviation, in comparison to the cash index. Overall, the series are asymmetric, with a small positive skewness, and have large kurtosis coefficients. The Jarque-Bera test statistics rejects the null hypothesis of normality for both price return indices. The ARCH test for heteroscedasticity points to the presence of ARCH effect in both index series. Also, the Ljung-Box test for autocorrelation evidences the presence of autocorrelation. These results corroborate the use of a multivariate GARCH model in assessing the volatility integration between cash crop and staple food markets. They are also in line with the underlying characteristics of commodity price movements, notably volatility clustering, as described in Deaton and Laroque (1992). With respect to the stationarity of the series, the Augmented Dickey-Fuller (ADF) and the Phillips-Perron (PP) tests reject the null hypothesis of non-stationarity at the 1 percent level of significance. The unconditional correlation between cash and staple food price index using the Pearson coefficient is estimated to be 0.74 at the 5 percent level of significance.

Table 1: Descriptive statistics of the price indices

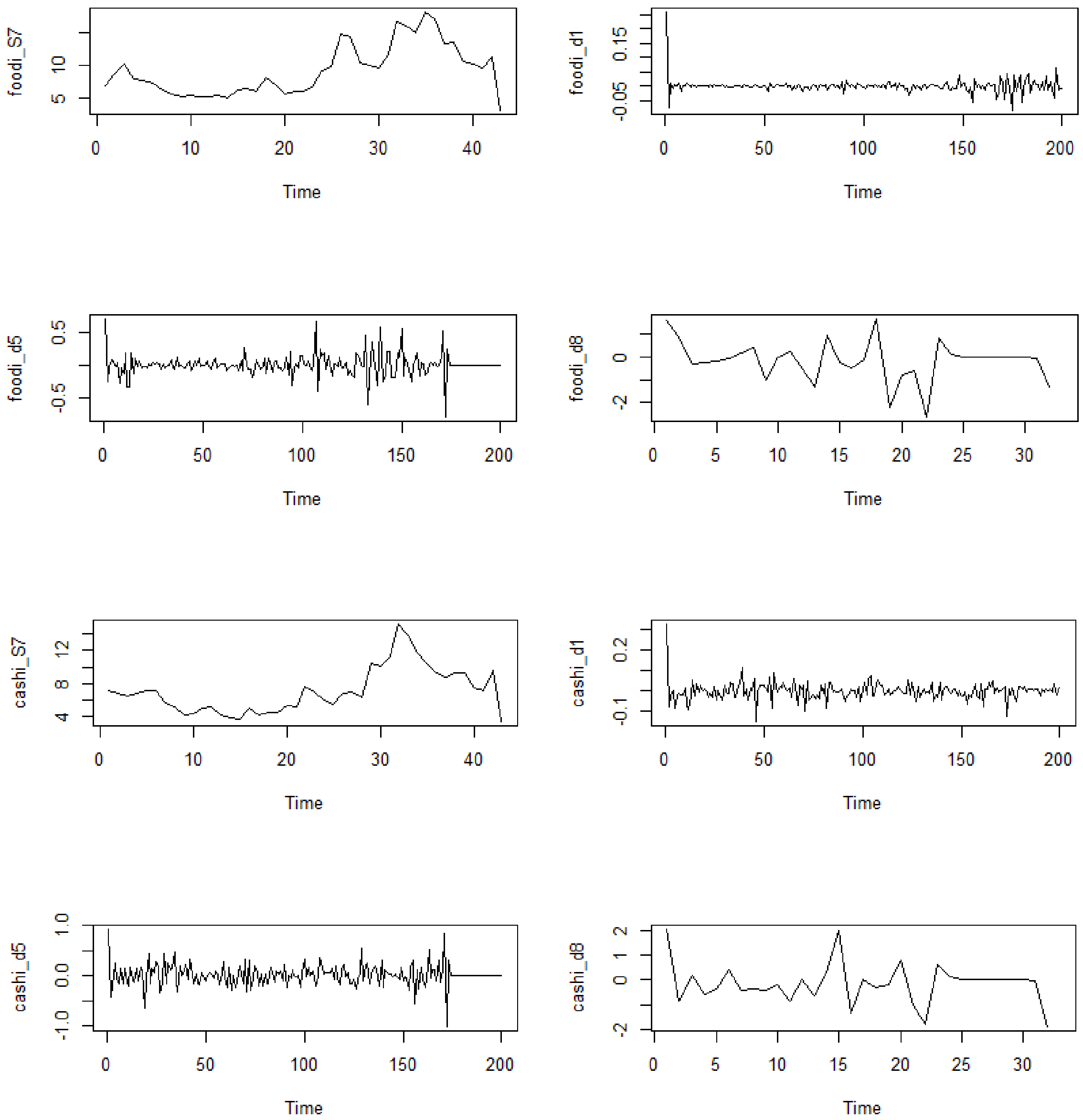
	Food index	Cash index
Mean (%)	0.0075	0.0053
Median (%)	-0.0247	-0.0117
Maximum	22.3032	71.1149
Minimum	-19.4870	-59.6080
Standard deviation (%)	2.3153	6.9209
Skewness	0.1380	0.6922
Kurtosis	8.6483	14.8098
Jarque-Bera	17081	50470
P-value	0	0
Q(14)	153.57	467.83
P-value	0	0
ARCH(14)	175	1176
P-value	0	0
ADF	-59.0660	-66.0250
P-value	0.010	0.010
PP	-86.0580	-104.3500
P-value	0.010	0.010

Notes: Q(14) refers to the Ljung-Box test for autocorrelation of order 14. ARCH(14) is the Engle (1982) test for conditional heteroscedasticity of order 14, while the Jarque-Bera test is used to test for normality. The Augmented Dickey-Fuller (ADF) and the Phillips-Perron (PP) methods are used to test for non-stationarity of the index series.

4.2 Results of the wavelet analysis

Figure 2 illustrates the outcome of a multiresolution analysis (MRA) at various scales for both food and cash price indices. For illustrative purposes we present 3 detailed series and 1 approximation series corresponding to the calculated values of the wavelet transform coefficients. A wavelet coefficient can be interpreted as the difference between two adjacent averages at a determined scale (Percival et al., 2004). Practically, it tells us how the average of a particular series changes when considering various scales (e.g. 2 days, 20 days, or 360 days). Analyzing the change in the average of price series at different scales helps detect any possible trends, discontinuities, or abrupt changes in the series. In figure 2, the highest scale level (frequency) component d1 corresponds to time-scale (frequency) of 2^1=2 days (daily effects), while d5 accounts for variations in a time-scale (frequency) of 2^5=32 days, capturing the monthly effects. The coarser, or smoother, part of the series (S7) captures the trend.

Figure 2: Wavelet decomposition results at selected scales for cash and staple food series



Note: foodi stands for food price index, while cashi represents the cash crop price index.

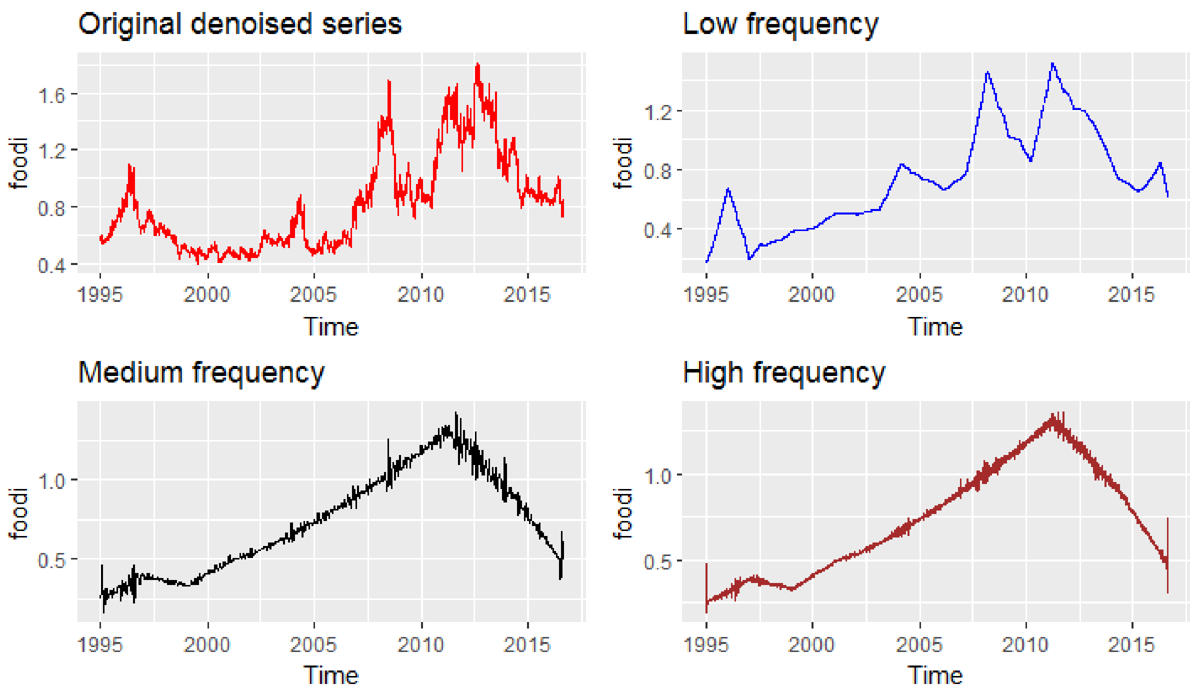
The MRAs in figure 2 suggests that the variations in the series are relatively heterogeneous across scales and time, with high fluctuations evidenced at finer scale resolutions for both cash and staple food series. Some localized features are interesting to point out. For example, a stretch of high volatility in the wavelet coefficients towards the end of the sample is revealed for the staple food index, while there are marked variances at the start and towards the end of the sample for the cash price index, as demonstrated by large fluctuations in the value of the wavelet coefficients. The smooth series for the cash and staple food series (S7 in figure 2) highlight the upward trend underlining both series up to their respective peak. Hence, the MRAs suggest that the fluctuations in the value of the wavelet transforms are heterogeneous across time and scales, implying that we can gain additional insights into the dynamics of the price series by considering their relationship at various scale levels.

After obtaining the wavelet transform values, we proceed by denoising the series, as described in the methodology section. Then, the series are reconstructed by adding to the trend, selected frequencies, or detail series, as described in equation 5. The selected scales (frequencies) are: 1) low-frequency (d=9), 2) medium-frequency (d=5), and 3) high frequency (d=1), as illustrated in figure 3 and 4. The original denoised series are also presented (top right figure 3 and 4). The objective from a selective wavelet reconstruction is to bring out parts of the series associated with bouts of high volatility at different frequency levels excluding distortions created by noise. Overall, the denoised series preserve the general trend patterns observed with the original cash and staple series.

A comparable trend pattern is observed when analyzing the series at the medium and high frequency levels, with both indices surging around the period of 2010-2011 and falling shortly afterwards. Some differences between the series emerge, however, when comparing volatility patterns within and between time-frequency domains. In the case of the food index, a stretch of extreme fluctuations spans from about 2007 to 2012, corresponding to the period of the recent financial crisis and food crisis. This is also evident when looking at the medium and high-frequency segments of the series (bottom left and bottom right, figure 3). Figure 3 also evidences a period of volatility between 1995 and 1997, which coincides with a period of high cereal prices due to tightening in world supplies and large fluctuations in prices in 1996/1997 (FAO, 1997). The cash index series displays a relatively much higher level of volatility than the food index at both the medium and high frequencies scales (figure 4). Three stretches of highly volatile periods are identified. The first one expands from around 1995 to 2001, as revealed by the reconstructed high-frequency portions of the series (figure 4, bottom right). The second long period of volatility runs from 2007 to 2012, coinciding with the global financial crisis and the surge in international food prices. The third period of volatility goes from about 2014 to 2016, concurring with the period of high and volatile cocoa and coffee prices.

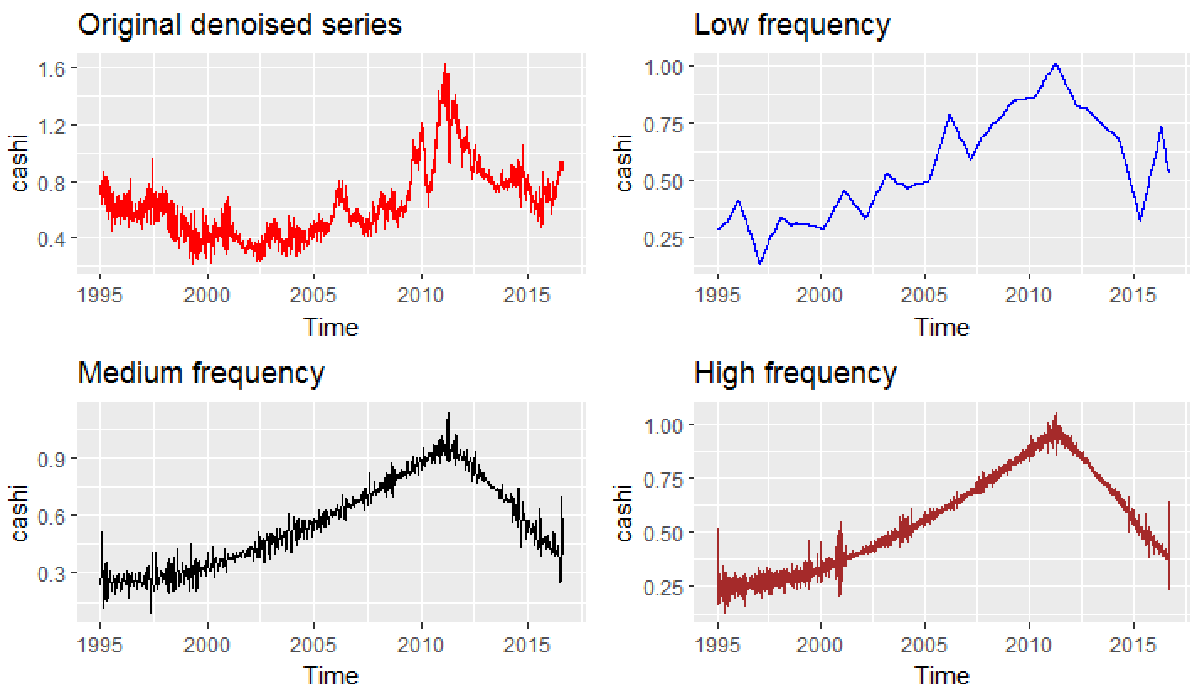
It is also possible to quantify how much each scale contributes to the overall variability of a series through scale-based variance decomposition as in Percival et al. (2004). The wavelet variance decomposition indicates that the largest contribution to the sample variance is accounted for by variations at the largest scale (long-run variations) for both the cash and food index. Hence, long-run variations have more weights on the series than short-run fluctuations.

Figure 3: Reconstructed staple food price series at selected scales



Note: foodi stands for food price index, while cashi represents the cash crop price index.

Figure 4: Reconstructed cash crop price series at selected scales



Note: foodi stands for food price index, while cashi represents the cash crop price index.

4.3 GARCH model

Using the staple food price return index and the cash crop price return index, we estimate 4 bivariate VAR-BEKK-GARCH models. The first model uses the original denoised series, as explained in the previous section, while the other 3 models are applied to the denoised series but for different scale frequencies: low-frequency (model 2), medium-frequency (model 3), and high-frequency (model 4). These models examine the volatility and mean transmission between cash and staples food returns at various time-frequency domains. The VAR specification describes the conditional mean of the model, while the GARCH component explores the volatility interactions. We apply the AIC and SIC information criteria to identify the optimal lag order of the VAR system and run univariate GARCH for both index series to which we apply the same information criteria to find the lag order for the GARCH component. The information criteria selects VAR(3) and GARCH(1,1) as the optimal specification. A comparative estimation of the log-likelihood values derived from other alternative lag specifications confirms the data is best characterized by a GARCH(1,1) specification.

The estimation results are reported in table 2, where food_ARCH and cash_ARCH stand for the past error terms of the food staples and cash crops, respectively. Food_GARCH and cash_GARCH, on the other hand, are the past conditional volatility terms associated with the food and cash price returns, respectively. The ARCH terms indicate whether the conditional volatility is driven by lagged innovations, while the GARCH estimates show if the current conditional volatility is influenced by its lagged values, reflecting volatility persistence. In general, estimation results from the 4 pair-wise bivariate VAR(3)-BEKK-GARCH(1,1) models reveal some similar patterns with respect to the estimated ARCH and GARCH coefficients. First, the coefficients are found significant for most of the pair-wise models. Second, the estimated values for the ARCH coefficients are generally lower than the GARCH estimates for cash and staple price returns, implying lagged shocks do not impact current conditional variance as much as lagged volatility values. The results also support the use of the BEKK-GARCH(1,1) approach in modelling volatility.

Table 2 also reports estimations for the mean price return equations specified as VAR. Results indicate that, generally, the own autoregressive parameters for both staple food and cash crop price return indices are found to be statistically significant. This suggests that one-lagged returns can predict current prices in the case of these commodity groups, implying short-term predictability. Results also show that some cross-market returns parameters are found positive and significant, but their number is much less than in the case of own mean spillover estimates. Also, we note that the information transmission flows mostly from the staple food to the cash markets, as shown by the number of significant coefficients capturing the effect of changes in staple food crop prices on cash crop returns.

Table 2: Estimates of VAR(3)-GARCH(1,1) for maize and cash crops

	Model 1		Model 2		Model 3		Model 4	
	Food	Cash	Food	Cash	Food	Cash	Food	Cash
Const_mean	0.00008	0.00004	0.00000	0.00000	0.00001	0.00000	0.00043	0.00031
	(-0.79899)	(0.96042)	(0.89922)	(0.82179)	(0.89976)	(0.98490)	(0.05702)	(0.62380)
Food_L_11	-0.15760	0.13147	1.17008	0.00111	1.06979	-0.00238	-1.26597	0.10419
	(0.00000)	(0.00081)	(0.00000)	(0.95734)	(0.00000)	(0.93741)	(0.00000)	(0.00374)
Cash_L_12	0.01039	-0.31182	0.01218	1.18186	-0.00758	1.05258	-0.00124	-1.32024
	(0.02633)	(0.00000)	(0.51049)	(0.00000)	(0.27306)	(0.00000)	(0.76342)	(0.00000)
Food_21	-0.05544	0.01952	-0.32255	0.00473	-0.27520	0.00186	-1.06454	0.07982
	(0.00006)	(0.62300)	(0.00000)	(0.88062)	(0.00000)	(0.96586)	(0.00000)	(0.06138)
Cash_22	0.00209	-0.13668	-0.00704	-0.33207	0.00113	-0.27921	-0.00151	-1.11225
	(0.66725)	(0.00000)	(0.80172)	(0.00000)	(0.90922)	(0.00000)	(0.77771)	(0.00000)
Food_31	0.01445	0.02158	0.14154	-0.00708	0.05592	-0.00208	-0.45706	0.07154
	(0.28800)	(0.58260)	(0.00000)	(0.73306)	(0.00011)	(0.94505)	(0.00000)	(0.02819)
Cash_32	0.00691	-0.07188	-0.00674	0.13733	0.00419	0.06490	-0.00652	-0.51512
	(0.13940)	(0.00000)	(0.71562)	(0.00000)	(0.54463)	(0.00001)	(0.11177)	(0.00000)
Const_variance	-0.00620	-0.00026	0.00004	0.00002	-0.00101	-0.00057	-0.00077	0.00287
	(0.00000)	(0.70992)	(0.00056)	(0.02690)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Food_ARCH_1	-0.35698	0.00462	0.61076	0.18253	1.64856	0.06783	-0.25576	-0.66311
	(0.00000)	(0.74829)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Cash_ARCH_2	-0.00777	-0.26071	0.20197	1.91974	0.01345	1.54109	-0.01475	0.49148
	(0.03806)	(0.00000)	(0.00000)	(0.00000)	(0.00897)	(0.00000)	(0.00000)	(0.00000)
Food_GARCH_1	0.89969	0.10501	0.03029	0.30491	0.40682	-0.01026	-0.96854	0.06036
	(0.00000)	(0.01739)	(0.00102)	(0.00000)	(0.00000)	(0.50439)	(0.00000)	(0.00000)
Cash_GARCH_2	0.00176	-0.96807	0.81977	0.49076	-0.09088	-0.56533	-0.00598	-0.86270
	(0.83238)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Dignostic tests								
AIC	-21799.56		-75342.12		-47452.4		-28805.31	
LB	26.92	97.356*	1104.4*	720.14*	5249.7*	3748*	1332*	1554.9*
LB2	28.657	36.371	14.59	5.5227	1163.3*	1076.1*	79.693	5157.8*
LM (ARCH)	24.939	36.662	13.607	4.9566	1000.8*	775.3*	430.54*	1729.9*
Market correlation	1	0.02	1	0.63	1	0.34	1	0.12
	0.02	1	0.63	1	0.34	1	0.12	1

Notes: A bivariate model VAR(3)-Full-Bekk-GARCH(1,1) model is estimated for each model from January 2, 1990 to August 28, 2016. The information criteria AIC and SIC were used to select the optimal lag order for the VAR model and the GARCH specification. Model 1: Original denoised series; model 2: Low frequency; model 3: medium-frequency; model 4: high frequency. LB and LB^2 is the Ljung-Box Q-statistic for standardized and standardized square residuals. P-values reported in parentheses. * stands for significant at the standard 5 percent level.

The diagonal elements of matrix A (see equation 7), capturing own shocks, and the diagonal elements of matrix G, associated with own GARCH effect, are mostly significant for the estimated models. That is, own news and past volatility movements affect the current conditional variance values. Also, a general assessment show that the off-diagonal elements of matrix A and G are for the most cases significant, but with some degree of variations, reflecting asymmetries in the dynamics. In terms of model 1, results are generally in line with those obtained with the other models. For the staple and cash crop equations, own ARCH and own GARCH terms are highly significant. In absolute terms, estimates of the ARCH coefficients were generally found much smaller than those obtained for GARCH, implying larger effects of past conditional variance than lagged innovations on current conditional variances. Also, model 1 returns the highest number of non-significant estimates than model 2, 3, and 4.

For model 2, results indicate that the current conditional variance for cash crop return indices depend on their own ARCH and own GARCH terms, meaning that market volatility of cash crops can generally be predicted on the basis of past shocks and past variance. However, in contrast to model 1, the own ARCH effect is found greater than own GARCH effect, suggesting that unexpected shocks play a much important role in driving variability of staple returns at low frequencies. Likewise, own ARCH estimate for staples and cash crop equations are found greater than own GARCH effects in model 3. For model 4, own GARCH effect is larger than own ARCH effect for both the staples and cash equation, in line with the result obtained with model 1. That is, at high frequencies, the condition variances of cash and staple returns are influenced by their respective past variances more so than unexpected news.

We now turn our attention to volatility transmission between staple food and cash crops, which is captured by the cross-estimates of ARCH and GARCH terms. Overall, there is significant volatility transmission between staple food crops and cash crops as evidenced by the number of significant cross effects terms estimated for the various pair-wise systems. We note that the cross-market GARCH estimates are generally much larger than those of the cross-market ARCH effects. This is an indication that the conditional volatility of cash crop (staple food) markets is largely influenced by periods of volatility in the staple food (cash crop) markets than the effects of lagged price return innovations in the staple food (cash crop) markets. Specifically, the GARCH cross-market effects are all significant, with the exception of model 1, where past volatility in the cash market does not affect the staple food market, and model 3 where the past volatility in the food market does not impact the cash market. On the other hand, the cross-market ARCH effects are all significant, with the exception of model 1, where past innovations in the staples market do not bear any influence on the volatility of cash crop returns. We note also that the cross-market estimates associated with the food market are generally larger than the cross-market estimates for cash crops, suggesting that past innovations and volatility staple returns have a much larger effects on the conditional volatility of cash crops. This is an indication that information coming from the staples market influences the cash crop market to a greater extent than the information originating from the opposite direction. Despite the bidirectional nature of the relationship, both the own GARCH and ARCH effects, are found mostly larger in magnitude than the cross effects, highlighting the dominant role of intrinsic factors.

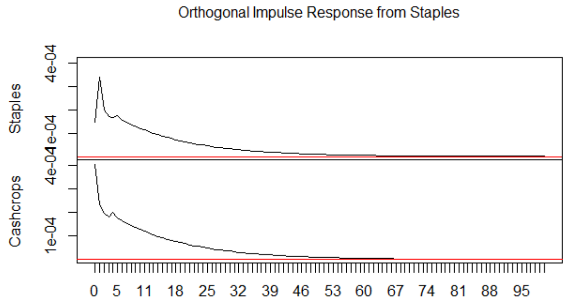
The diagnostic tests carried out on the standardized residuals and squared standardized residuals show a significant reduction in ARCH effects and autocorrelation depicted in the return series (see table 1), indicating that the estimated models are sufficiently flexible to describe the volatility dynamics between staples and crop returns. The estimated Pearson correlations are also significant and larger in model 2 than in other models. That is in the long-run, the change in the average of the staple and cash crop return series appear to be highly and significantly correlated.

4.4 Impulse response

Using the estimated conditional variations in model 2 and 4, we further explore the volatility interaction between cash and staple by computing the impulse response functions. This is obtained by simulating the response to unexpected orthogonal shock in one of the markets, as illustrated in figure 5 and 6. For model 2, an innovation in the staple market has a large initial effect on the cash market but the effect is relatively not persistent. Following an initial shock, the effect on the cash market disappears after about 2.5 months. Similarly, an unexpected shock from the cash market has a relatively large initial effect and tends to dissipate gradually after 2.5 months. Also, the figure shows that a shock in the cash market has a larger impact on the volatility of cash returns than on the volatility of the staples. The fact that cash crop and staple food markets adjust relatively rapidly to unexpected shocks suggests that market participants process and adjust rather quickly to price signals.

Results of the impulse response analysis with respect to model 4 show somewhat similar results than model 2. As figure 6 illustrates, an unexpected shock in the staples results in a high initial effect on the cash market, but in contrast to model 2, the effect tends to decay rather slowly lasting over a period of 2 years. On the other hand, an innovation in the cash market has a high initial effect on its own market, but the impact on the staple is relatively week. This last result highlights further the findings of the BEKK-GARCH model, where the magnitude of the estimated cross market GARCH and ARCH effects in the staples equation is relatively low. Therefore, an innovation corresponding to the high frequency portion of the cash return series has a relatively subdued effect on the volatility of the staple food returns. In contrast, an unexpected shock in the volatility of staples series has a larger effect on cash returns variability at high frequency levels.

Figure 5: Impulse response functions based on model 2



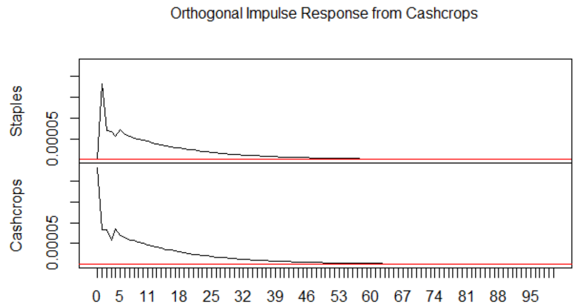
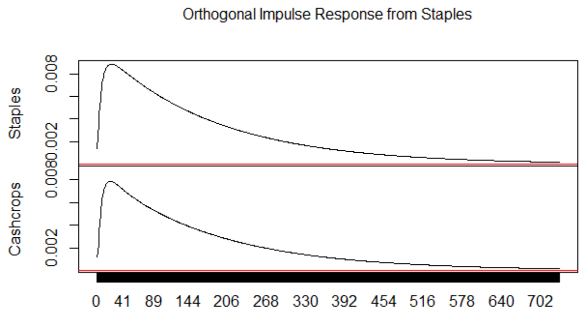
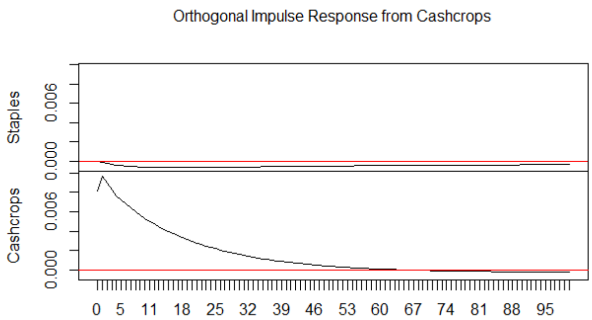


Figure 6: Impulse response functions based on model 4





5 Conclusion and implication

The analysis carried out in this paper examines the volatility interaction between staple food and cash crop futures prices returns. As opposed to the vast majority of studies that focus on national and farm level analysis, we look at the relationship at an international market level. The price dynamics between these commodity groups is relevant for the developing countries that depend on cash crop export earnings to sustain food imports. We apply a BEEK-GARCH framework supplemented by a wavelet analysis to locate precisely marked periods of volatility bouts and changes in the dynamics at different time horizons. Overall, the results indicate significant levels of interdependence between cash crop and staple food futures, with prevailing asymmetric volatility transmissions. Information is found to take place mostly from the staple food to the cash crop markets across different time scales.

The co-movement and the overall bidirectional volatility between cash crops and staples futures returns reflect changes in macroeconomic, financial, and fundamental factors. Several studies attribute the co-movement between various agricultural markets to the phenomenon of financialization of commodities (Basak and Pavlova, 2016; Grosche and Heckelei, 2016). The driving force is the expectation by investors that holding commodity assets offers diversification opportunities, as part of a well-balanced risk-return investment strategy. In the long run, however, co-movement between staples and cash crops can reflect changes in factor input costs at production level, notably labor cost. Indeed, Acharya et al., (2013), Gorton et al., (2013), and Routledge et al., (2000) provide empirical evidence of the linkages between futures and spot prices for storable commodities such as coffee and cocoa.

Results of our analysis convey some implications from both an investment and policy making perspective. Because the correlation between cash and staples is found relatively weaker in the short run, investors can use cash crop futures as a hedge to holding staple food as investment assets. Also, because of the significant cross-market effects running mostly from staple to cash, investors can use information provided by staples futures to help forecast cash crop futures returns. From a policy perspective, the weaker correlation indicates that cash crop export earnings do not contribute significantly to hindering the impact of short-term high food international prices, in comparison to the long run. Hence, where a cash crop exporting developing country relies heavily on earnings from cash crop trade to pay for food imports, short-term measures may be required to finance import bills. In the long run, however, the relatively higher correlation and significant cross market effects suggest that investors cannot use cash crops assets as hedge against holdings of staples. From a policy perspective, the stronger correlation means that cash crop and staple futures move together, suggesting that cash crops earnings could potentially limit, or offset, rises in international food prices. The inelastic nature of cash crop markets means that the rate of increase in cash crop prices more than offset the decline in export quantities. Also, because of the stronger correlation and significant cross market effects in the longer term, cash crop exporting countries could deploy support policies targeted at the cash crop sub-sector, when staple food returns rise relative to those of cash crops. When cash price return start to increase, pulled up by staples, the support policy measures can be relaxed.

Finally, while we apply a discrete wavelet transform (DWT) to reconstruct the series into various time scales, the use of a continuous wavelet transform (CWT) approach does not require the arbitrary selection of time scales and accounts endogenously for the presence of structural breaks. A CWT approach enables the measurement of the correlation between staples and cash crop returns in a continuous time-frequency domain. Future research could examine the interaction between cash crop and staples returns using CWT and compare the results with those obtained by the DWT. For these results to be translated at country level, an assessment of the transmission of futures prices to export prices and import prices is warrant. This will help anticipate the extent to which cash crop export earnings can cover for food import bills given the volatile nature of international agricultural commodity markets.

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