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Abstract

This paper investigates the price dynamics between a selection of international staple food and cash crop futures prices. This price interaction is particularly relevant for developing countries that rely on cash crop export earnings to finance their staple food import requirements. We employ a multivariate Copula-DCC-GARCH model to characterize the cash crop and staple food price interaction over time and a rolling-sample volatility index to identify the direction of the volatility spillover for staple-cash commodity pairs. Results show that the intensity of interaction varies considerably over the sample time, but is, generally positive, and stronger during the period 2007-2012 associated with high commodity prices and financial market stress.

Keywords: Volatility spillover, Copula-DCC-GARCH, forecast error variance decompositions, cash crops, staple food crops

JEL classification: Q13, C13, G11, G01

1 Introduction

The run-up in agricultural international commodity prices over the past decade remains a subject of much animated debates and vivid research. One particular question is over the ability of net food importing developing countries (NFIDCs) to sustain food procurements amid rising food import bills, at least in the short-run (IMF, 2008). Chiefly, rising food imports bills require adequate levels of foreign reserves to secure food products on the international markets.

The recent 2007-2011 surge in world food prices occurred against the background of a general boom in international commodity prices (Gilbert, 2010; Headey and Fan, 2008; Tadesse et al., 2014; Trostle, 2008). The World Bank energy commodity index rose by 278.3 percent between 2002 and 2008, while during the same period, the non-energy index increased by 136.8 percent, including a 102.9 percent increase for the agricultural sub-index. A similar observation emerges when looking at cash crop products such as coffee, tea, cocoa, sugar, and cotton. International coffee prices, for example, went up by 26 percent between 2006 and 2009, while prices for tea and sugar increased by 45 percent and 23 percent, respectively. The rise in cash crop commodity prices along with food prices implies that export earnings of the commodities that many low income food importing countries rely on could potentially contribute to, partially, or even fully, offset the increase in the food import bills. The extent to which rising cash crop earnings can offset increasing food import bills depends, inter-alia, on their contribution to a country's GDP, the price elasticities of the international demand and supply for cash crops, currency movements, and the transmission of world futures to local markets. Futures prices, such as those negotiated at the Intercontinental Exchange (ICE) and the Chicago Board of Trade (CBOT), are relevant because they are often taken as the world reference price. As such, they can influence border prices, and hence, the value of import bills and export earnings (Chen et al., 2009).

The apparent positive correlation between cash and staple food futures prices is difficult to explain on the basis of market fundamentals only, at least in the short-run. Indeed, the substitution possibilities in consumption and production between cash and staple food crops in the physical market are rather limited and therefore cannot explain the extent of price correlation. However, macroeconomic related factors, weather shocks affecting major producers of both commodity groups, movements in energy prices, and institutional investors diversifying their assets away from equities and other financial assets by investing in commodity futures, constitute some common factors that could cause prices to correlate. The effect of financial investments on commodity market remains, however, a subject of ongoing debate. Irwin and Sanders (2011), Fattouh et al. (2012), and Hamilton and Wu (2015), argue that institutional investors don't have any impact on commodity futures prices.

In this paper, we examine the magnitude of interdependence and the dynamics of volatility across a selected sample of cash and staple food international futures prices, in the context of financialization of commodity markets. We use a Dynamic Conditional Correlation (DCC)-Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model to assess the extent of the interaction between both commodity groups. The use of a DCC-GARCH framework allows a description of the evolution of the time-varying correlation between food and cash crop futures prices. In addition, we augment the DCC-GARCH specification with a student-t copula to account for the tail dependence that underlines the price series. We then compute spillover indices based on the generalized forecast error variance (GFEV) decompositions, as recently suggested in Diebold and Yilmaz (2012), to explore the underlying dynamics and trace volatility spillovers across markets.

Our analysis contributes to the existing research in several aspects. First, the trade-off between cash crops and staple foods has been extensively researched at farm and national level, but analysis at international market level is lacking. We contribute to filling this gap by characterizing the evolution of short-term interdependence and volatility dynamics between these two commodity groups in the international futures markets. Second, the analysis covers a period extending from 1990 to 2016, which allows assessing the impact of the recent surge in food prices 2007/2008 and 2011, the global financial crisis of 2007/2008, as well as the period of end-1990 and beginning 2000 when cash crop futures prices were depressed and touched historical lows in real terms (e.g. coffee). Third, we combine two different methodologies for assessing volatility dynamics, namely the

DCC-GARCH and the rolling-sample volatility index, and relate their results. Also, the use of rolling-sample allows us to take into account potentially different regimes, or structural breaks, over the sample period. The reminder of the paper is structured as follows: the next section provides a review of methodologies to investigate short-term market interdependence, followed by a discussion on the methodology and data used in our empirical analysis. Subsequently, we present and discuss the main results. The final section provides a summary of the main conclusions and some ideas for future research.

2 Methodologies for investigating short-term commodity market interdependence

The literature on the relationship between international prices of cash crop and staple food is rather scarce. Most of the studies involving cash crop and staples are more concerned with medium-to-long-term relations, with a particular focus on farm resource allocation in the presence of input constraints (Norton and Hazell, 1986). The focus on the trade-off between cash crop vs staples food production is motivated by food security concerns. Indeed, some argue that food security of smallholder farm households may be at risk when farm resources are assigned to cash crop production (Maxwell and Fernando, 1989; Mittal and others, 2009), while others sustain that cash production provides the means to secure food access - i.e. the access dimension of food security (Timmer, 1997; Von Braun and Kennedy, 1986; Weber et al., 1988). Recent research in this field shows that cash crop and food staple can actually play a complementary role (Govereh and Jayne, 2003; Theriault and Tschirley, 2014).

While the literature on the linkages between cash crop and staple food international prices remains limited, the use of GARCH framework to investigate the interdependence among markets has been quite extensive. For example, Olson et al. (2014) use the Baba, Engle, Kraft and Kroner BEKK-GARCH framework to analyze the volatility integration between energy and equity markets and find that equity markets response modestly to shocks in the energy markets, and that correlation is low between these markets, with the exception during the financial crisis (2008-2010). Using a VAR-GARCH model, introduced by Ling and McAleer (2003), Mensi et al. (2013) study the price return and volatility ties between the S&P 500 index and commodity price indices for energy, food, gold, and beverages over the period from 2000 to 2011. Their model estimates the effect of unexpected shocks, or news, on the S&P 500 index and the impact on the agricultural markets. Results confirm the already large body of evidence on the significant price return and volatility interactions between the equity and commodity markets.

Gao and Liu (2014) also apply bivariate GARCH models to investigate the volatility connection between the S&P 500 index and a set of commodities. Their models are augmented with regime switching to account for changes in the long-run relationships. Results show that regime switches in the energy complex appear to be driven by volatility in the equity market rather than volatility in the grains market. They also reveal significant scope for risk diversification between certain commodity groups. Gardebroek and Hernandez (2013) use a BEKK and a dynamic conditional correlation (DCC) trivariate GARCH approach to evaluate the volatility spillover among maize, crude oil, and ethanol spot prices. Model results indicate a unidirectional volatility spillover running from maize to ethanol. Similar results are obtained by Trujillo-Barrera et al. (2012) with the use of a BEKK-GARCH specification. Other studies employing a GARCH approach to assess price volatility between various commodities include Chang and Su (2010), Ji and Fan (2012), and Harri and Hudson (2009). Likewise, Serra (2011) examines the relationship between food and energy market, with a focus on the price linkages among crude oil, ethanol and sugar and detects only a limited effect of ethanol on price movements of sugar and crude oil. Also, using a multivariate GARCH applied to a sample of 28 commodities, Vivian and Wohar (2012) identify significant volatility linkages and volatility persistence even after accounting for structural breaks. A similar research is undertaken by Al-Maadid et al. (2017) to look at the mean and volatility spillover between food and energy markets. Results indicate significant cross-market effects, particularly during the recent food crisis and the 2008 financial crisis. Similarly, Nazlioglu et al. (2013) undertake an examination of price volatility between crude oil and a sample of commodities including wheat, maize, sugar, and soybeans. Their research demonstrates that volatility transmission from energy markets to agricultural markets is statistically significant only after 2006. On the other hand, Aepli et al. (2017) use multivariate dynamic copulas DCC-based models to explore the time-varying dependence structure of commodity futures portfolios. They find that copula functions are most suitable specification to model dynamic dependence across markets. Other studies using a DCC approach include Chiang et al. (2007), Celık (2012), Bicchetti and Maystre (2013), Lombardi and Ravazzolo (2016), and Roy and Sinha Roy (2017).

Most of the GARCH studies mentioned so far are estimated under the assumption of a multivariate normal distribution of the variables. However, distributions of asset price returns, and those of commodities in particular are generally skewed and leptokurtic - features that a joint normal distribution does not capture. To model these specific data characteristics, the use of copula distributions is quite handy. Model estimated using joint copula distributions provide a better empirical fit than standard normal multivariate distributions (Breymann et al., 2003; Demarta and McNeil, 2005). The concept of copulas was introduced by Sklar (1959) but only applied recently to a wider range of areas including environmental and financial studies. Patton (2006) introduced copulas with time-dependent parameters to model exchange rate dependency, while Jondeau and Rockinger (2006) used the skewed Student-t copula to investigate the daily market returns. Bartram et al. (2007) use time-varying copula to model the dependency among 17 European stock markets. A number of convenient copula functions have been developed to address certain distributional features. A complete review of copulas can be found in Manner and Reznikova (2012).

3 Methodology and data

3.1 *GARCH approach*

The Autoregressive Conditional Heteroscedasticity (ARCH) and GARCH models are well known methodologies for modelling volatility. In this study, the empirical approach is based on estimating a DCC-GARCH model for 3 staple food futures price returns series (maize, wheat, and soybeans) and 4 cash crop futures price returns series (coffee, cocoa, cotton, and sugar). We begin by specifying the conditional mean equation, commonly represented as a reduced form of a VAR:

$$A(L)r_t = \varepsilon_t \ , \tag{1}$$

with $\varepsilon_t|\omega_{t-1} \sim N(0, H_t)$ where $A(L)$ refers to a 7 x 7 polynomial matrix in the lag operator L, r_t is a 7 x 1 daily return vector at time t, and ε_t a 7 x 1 corresponding vector of random errors, representing the shocks, or innovations. H_t represents a 7 x 7 conditional variance-covariance matrix conditional on market information ω_{t-1} available at t-1. Given the large number of variables involved in the analysis, and to facilitate parameter estimation, we select the DCC-GARCH type model. This specification enables the measurement of conditional variances and conditional correlations, while ensuring the positive definiteness of $\mathrm{H_t}$ and easing model conversion. As in Engle (2002) and Gardebroek and Hernandez (2013), we apply the DCC model to parameterize the conditional variance-covariance matrix $\mathrm{H_t}$ as:

$$\mathrm{H_t = D_t R_t D_t} \tag{2}$$

where $\mathrm{D_t = diag(h_{11t}^{\frac{1}{2}} +, \ldots., h_{77t}^{\frac{1}{2}})}$ and each $\mathrm{h_{ii,t}}$ is described by a univariate GARCH model such as a GARCH(1,1) where $\mathrm{h_{ii,t} = w_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{ii,t-1}}$. Further,

$$\mathrm{R_t = diag(q_{iit}^{\frac{1}{2}} +, \ldots., q_{NNt}^{\frac{1}{2}})^{-1/2} Q_t diag(q_{iit}^{\frac{1}{2}} +, \ldots., q_{NNt}^{\frac{1}{2}})^{-1/2}} \tag{3}$$

where $\mathrm{Q_t}$ is a 7x7 symmetric positive definite matrix and is populated as:

$$\mathrm{Q_t} = (1 - \alpha - \beta)\overline{\mathrm{Q}} + \alpha(u_{\mathrm{t-1}}u'_{\mathrm{t-1}}) + \beta\mathrm{Q_{t-1}}, \tag{4}$$

with the standardized residuals defined as $u_{\mathrm{t}} = D_t^{-1}\varepsilon_t$, and the positive adjustment parameters $\alpha + \beta < 1$, and $\overline{\mathrm{Q}}$ being a 7x7 unconditional correlation of $\mathrm{u_t}$. The estimation of the DCC model is carried out by maximum likelihood and, hence, requires the specification of a likelihood function. We assume that the multivariate joint distribution follows a student-t copula to account for the leptokurtic distribution of the price series (see Table 2). As in Kim and Jung (2016),the density function of the student-t copula can be expressed as:

$$c_{\mathrm{t}}(\mathrm{u_{it}}, \ldots, \mathrm{u_{nt}}|\mathrm{R_t}, \delta) = \frac{\mathrm{f_t}(\mathrm{F_i^{-1}}(\mathrm{u_i}|\delta), \ldots, \mathrm{F_n^{-1}}(\mathrm{u_{nt}}|\delta)|\mathrm{R_t}, \delta)}{\prod_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{f_i}(\mathrm{F_i^{-1}}(\mathrm{u_i}|\delta)|\delta)} \tag{5}$$

where $\mathrm{u_{it}} = F_{it}(r_{\mathrm{it}}|\mu_{\mathrm{it}}, h_{\mathrm{it}}, \varphi_{\mathrm{t}}, \delta_{\mathrm{it}})$ is the probability integral transformed values by F_{it} estimated with the first stage GARCH process, $F_i^{-1}(u_i|\delta)$ refers to the quantile transformation, $f_t(.|R_{\mathrm{t}}, \delta)$ is the multivariate density of the student distribution with conditional correlation R_{t} and shape parameter δ, and $f_i(.|\delta)$ are the univariate margins of the multivariate student distribution with δ taken as the common shape (Kim and Jung, 2016; Ghalanos, 2015). Finally, the joint density is composed of (1) the copula density function and (2) the marginal distribution functions associated with the univariate GARCH estimation and can be expressed as in Kim and Jung (2016):

$$\mathrm{f}(r_{\mathrm{t}}|\mu_{\mathrm{t}}, h_{\mathrm{t}}, R_{\mathrm{t}}, \delta) = c_t(\mathrm{u_{it}}, \ldots, \mathrm{u_{nt}}|R_{\mathrm{t}}, \delta) \prod_{i=1}^{n} \frac{1}{\sqrt{h_{it}}} f_{it}\,(u_{it}|v_{\mathrm{i}}, \varphi_{\mathrm{i}}) \tag{6}$$

We use the R package rmgarch (Ghalanos, 2015) to implement and estimate the Copula-DCC-GARCH model and select the function *solnp*, for general nonlinear programming problems developed by (Ye, 1987), as the solver.

3.2 *Spillover indices*

To estimate the volatility transmission across markets, we compute spillover indices based on the generalized forecast error variance decomposition, as described by Diebold and Yilmaz (2009). The generalized form of the FEVD does not depend on variable ordering, as illustrated by Koop et al. (1996) and Pesaran and Shin (1998). For every h-step-ahead forecast, we can decompose the total variance of the error forecast for variable i into shocks due to i and those due to variable j. The variance contribution matrix (VCM) contains these estimates, θ_{ij}, and where the row elements of the matrix add to unity:

$$\theta_{ij}(h) = \begin{bmatrix} \theta_{ii}^{h} & \cdots & \theta_{ij}^{h} \\ \vdots & \ddots & \vdots \\ \theta_{ji}^{h} & \cdots & \theta_{jj}^{h} \end{bmatrix}, \text{ and i, j} = 1,2,3,\ldots,N. \quad (7)$$

The diagonal elements of $\theta_{ij}(h)$ show the contribution of own shocks to the variance of the forecast error of variable i, while the elements off-diagonal show the contribution of the various shocks due to j, or spillover, with j≠i. As defined by Diebold and Yilmaz (2012), and illustrated by Grosche and Heckelei (2016), a series of time-varying volatility spillover indices can be computed. In this paper, we make use of two main indices: 1) total spillover, and 2) net pairwise spillovers, as described in the following:

$$S(h) = \frac{\sum_{i,j=1,i\neq j}^{N} \theta_{ij}(h)}{N} * 100 \quad (8)$$

Equation (8) represents the *total spillover* index $S(h)$, which calculates the share of volatility spillovers across N variables h-step ahead in relation to the total forecast error variance. On the other hand, *net pairwise spillover* between market i and market j is the difference between the gross volatility shocks from market i to market j and those originating from market j to market i and is described as:

$$S_{ij}(h) = \frac{\theta_{ij}(h) - \theta_{ji}(h)}{N} * 100 \quad (9)$$

As opposed to the DCC-GARCH approach, the main advantage of the rolling-sample volatility index method is that it produces spillover estimates across different markets. Table 1, shows some of the main differences between both methodologies.

Table 1: Main differences between DCC and volatility index approach

	Dynamic Conditional Correlation	**Directional Volatility Index**
Volatility measure	*Conditional variance*	*Range*
Spillover effect	*Only own effects*	*Own and spillover effects*
Estimation	*Provides significance levels for the cross-market volatility estimates*	*Does not provide significance levels for the cross-market volatility estimates*
Conditional mean estimation	*Full sample VAR*	*Rolling VAR*

3.3 *Data*

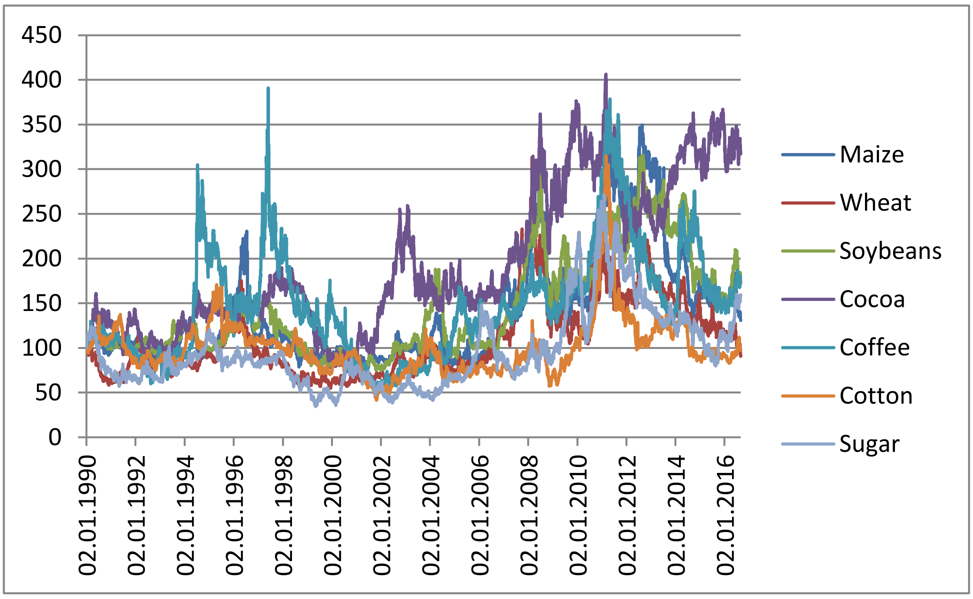
Using the FAOSTAT[1] database, the choice of the commodities included in this study is based on a pre-analysis that involves identifying the top exported cash crops and the top imported staple foods by the NFIDCs group. We then select those crops for which an international futures contract exists. On this basis, coffee, cocoa, cotton, and sugar futures prices are selected to represent the group of cash crops, while wheat, corn, and soybeans futures prices are chosen to represent the staple food group. We consider a sample composed of the Chicago Board of Trade (CBOT) corn (C1) futures, soybeans (SB1) futures and wheat (W1) futures, and the Intercontinental Exchange (ICE) sugar No. 11 (SB) futures, cocoa (CC) futures,

[1] http://www.fao.org/faostat/en/#data

coffee “C” (KC) futures, and cotton No.2 (CT) futures. Daily prices are obtained from Bloomberg and cover the period of January 2, 1990 to August 30, 2016 for a total of 6740 observations. The DCC-GARCH formulation is carried out on the returns of the series by taking the difference in the logarithm of two consecutive futures prices.

Figure 1: Daily prices of selected cash and staple food commodities

(01/01/1990 = 100)



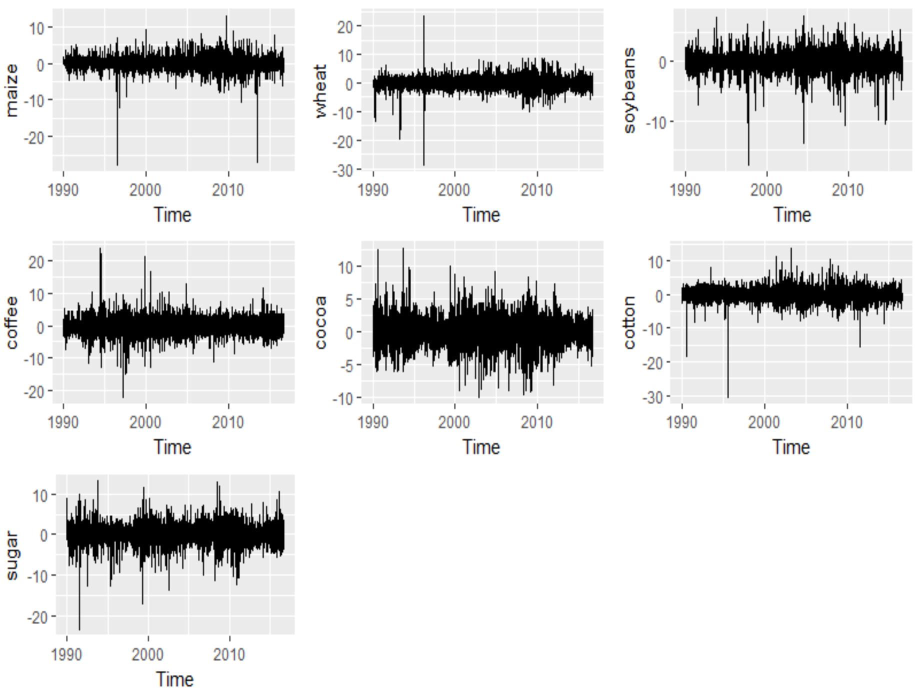
Source: Bloomberg

Figure 1 represents the daily prices of the seven selected futures price series (i.e. wheat, corn, soybeans, coffee, cocoa, cotton, and sugar) in index form. The graph illustrates the relatively elevated fluctuations that characterize these markets with frequent price spikes, over the sample period, particularly during 2007 and 2012. Overall, international cash and staple food prices increase steadily between 2002 and 2008, before a steep fall following the global financial crisis. They surge again in 2010 and 2011 but continuously decline in the period that followed, with a notable price spike for maize in 2012. Cocoa quotations, however, remain elevated between 2012 and 2016. The graph also suggests the presence of periods when international staple food and cash crop futures prices are highly correlated and moments when price co-movements are weaker. Figure 2 illustrates the changes in daily price returns for each of the commodities.

3.4 *Descriptive statistics*

The descriptive statistics of the seven price return series are reported in table 2. The statistics show that coffee offers the highest daily return followed by soybeans and sugar. Wheat shows the lowest daily return over the sample period. While coffee displays the highest daily return, it also has the highest standard deviation (2.4 percent), followed by sugar, wheat, and cocoa, with soybeans showing the lowest standard deviation (1.5 percent). When taking into account the risk factor, cocoa shows the highest value in terms of risk-adjusted returns, followed by soybean and coffee. Overall, the series are asymmetric, with negative skewness coefficient for

Figure 2: Daily price returns of selected cash and staple food commodities



corn, soybeans, cotton, wheat, and sugar, and positive skewness for only two series, coffee and cocoa.

Table 2: Descriptive statistics of futures price return series

	Maize	*Wheat*	*Soybeans*	*Cotton*	*Coffee*	*Cocoa*	*Sugar*
Mean (%)	0.004	-0.001	0.008	0.000	0.009	0.017	0.007
Median (%)	0.000	0.000	0.046	0.000	0.000	0.000	0.000
Maximum	12.760	23.300	7.629	13.620	23.770	12.740	13.210
Minimum	-27.620	-28.610	-17.430	-30.440	-22.060	-10.010	-23.490
Standard deviation (%)	1.710	1.930	1.550	1.810	2.400	1.910	2.160
Skewness	-1.140	-0.490	-0.930	-0.850	0.170	0.080	-0.430
Kurtosis	21.210	14.720	7.850	16.840	7.470	2.680	5.830
Jarque-Bera	127820	61199	18275	80455	15724	2027	9755
P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Q(14)	28.540	24.141	27.252	37.319	31.158	27.578	44.571
P-value	0.012	0.044	0.018	0.000	0.005	0.016	0.000
ARCH(14)	42.191	711.320	321.700	46.878	445.520	185.420	150.110
P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ADF	-57.840	-59.400	-57.490	-56.980	-60.020	-58.650	-61.380
P-value	0.010	0.010	0.010	0.010	0.010	0.010	0.010
PP	-78.948	-83.443	-80.438	-77.192	-83.285	-82.701	-83.138
P-value	0.010	0.010	0.010	0.010	0.010	0.010	0.010

Notes: Q(14) refers to the Ljung-Box test for autocorrelation of order 14, while ARCH(14) is the Engle (1982) test for conditional heteroscedasticity of order 14. Normality is tested using the Jarque-Bera test for normality. Test for non-stationarity is carried out using the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test.

The kurtosis coefficients for the series are all larger than the normal distribution, indicating that the probability of observing price peaks is higher than that under the assumption of a normal distribution. In fact, the results of the Jarque-Bera test confirm the rejection of normality for all the daily return series. Also, the Ljung-Box test for autocorrelation applied to the price return series points out evidence of autocorrelation. The ARCH test for heteroscedasticity evidences the present of ARCH effect for all the 7 seven series, supporting the use of multivariate-type GARCH models to examine the conditional volatility and volatility transmission between the various series. Finally, the stationarity property of the series is tested using the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test. Results show that the daily price return series are stationary, with the null hypothesis of a unit root strongly rejected at the 1 percent level of significance. Table A1 in the Appendix, reports the Pearson correlations of the price return series.

4 Empirical results

4.1 *Results of the Copula-DCC-GARCH model*

Using the 3 staple food price return series (maize, wheat, and soybeans) and the 4 cash crop price return series (coffee, cocoa, cotton, and sugar), we first estimate a 7 dimension VAR system. The VAR specification depicts the conditional mean of the DCC-GARCH model. We use the AIC and SIC information criteria to select the optimal lag order for the VAR system, while for the GARCH system, we run univariate GARCH models for each of the 7 return series to which we apply the AIC and SIC information criteria to select the lag order. The information criteria identifies VAR(1) and GARCH(1,1) as the optimal specification. A comparison of the log-likelihood values obtained from various alternative lag specifications shows that the data is best captured by a DCC(1,1) specification.

Table 3 presents the estimation results of the DCC model. The model shows the extent to which the correlation across staple food and cash crop markets changes over time. The top panel of the table represents the estimation results for the conditional mean return equation. It indicates that one-lagged returns estimates are not statistically significant (5 percent level) in predicting current price returns in the case of wheat, coffee, cocoa, and sugar. In contrast, maize, soybeans, and cotton respond to own autoregressive parameters, implying short-term predictability. The results also highlight few cases of mostly unidirectional cross-market mean spillovers (e.g. maize to coffee, soybeans to sugar, and wheat to maize). A bidirectional mean transmission is found between soybeans and wheat markets, underlining the strong substitution linkages between the two crops. In the cases of significant cross-market effects, the estimated coefficients are larger for the staples than cash crops, suggesting that information transmission flows mostly from staple food to cash market.

Table 3 also shows result of the conditional variance estimations obtained by running univariate GARCH models. ARCH_1 represents the past error terms of one of the food staples or cash crops. GARCH_1, on the other hand, represents the past conditional volatility terms of one of the food staples or cash crops. In general, estimation results show some common patterns associated with the ARCH and GARCH coefficients. First, these estimates coefficients are highly significant for most of the univariate GARCH equations. Second, the ARCH estimates are generally lower than those obtained for GARCH, indicating that lagged shocks do not influence current conditional variance as much as lagged values of volatility for these markets. These results are in line with the volatility clustering feature that characterizes commodity prices (Deaton and Laroque, 1992) in addition to supporting the use of GARCH(1,1) in modelling volatility persistence.

The estimated adjustment parameters α and β are significant at the 5 percent level, a result confirmed by the Wald test, which rejects the null hypothesis that the adjustment parameters are jointly equal to zero. Also, the sum of α and β is fairly close to 1, indicating high persistence in the conditional variances. Evidence against the assumption of a constant conditional correlation is further provided by the Engle and Sheppard Test of Dynamic Correlation (2001), which tests $R_t = R$. The test rejects the null hypothesis of constant conditional correlation. Table 3 displays some diagnostic statistics for the standardized residuals of the estimated DCC model. These confirm the adequacy of using a MGARCH. The Ljung-Box (LB), Lagrange Multiplier (LM), and Hosking Multivariate Portmanteau (HM) test statistics for up to 6 and 14 lags show no evidence of autocorrelation, ARCH effects, and cross-correlation, respectively.

Table 3: Copula-DCC-GARCH model estimation

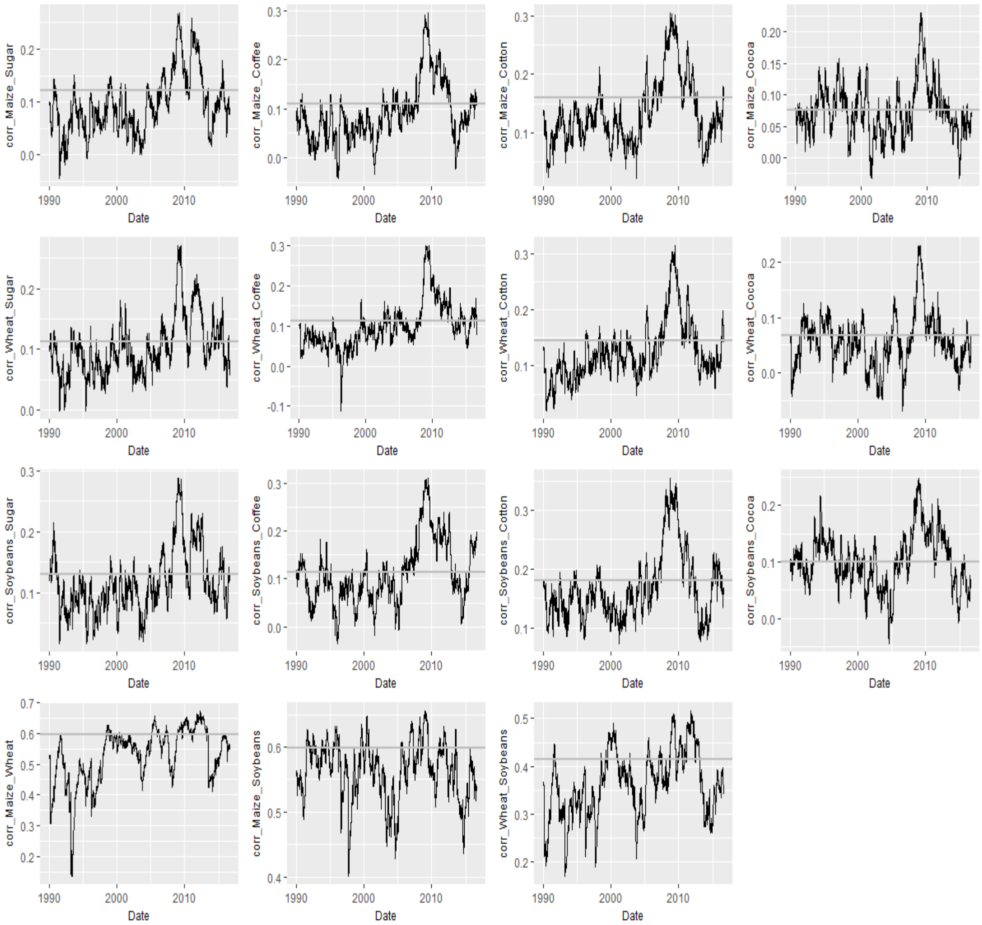
	Maize	Wheat	*Soybeans*	Coffee	*Cocoa*	Sugar	*Cotton*
Conditional mean equation							
Const_mean	0.000036	-0.000013	0.000077	0.000085	0.000173	0.000053	-0.000005
	(-0.862965)	(0.956263)	(0.682785)	(0.772745)	(0.457230)	(0.839375)	(0.981342)
Maize_l1	0.054839	0.028982	-0.019502	0.010552	0.037099	0.013944	0.008409
	(0.000727)	(0.110465)	(0.179806)	(0.640860)	(0.038869)	(0.492750)	(0.622101)
Wheat_l1	-0.020439	-0.023362	-0.033290	0.023505	-0.009255	-0.018694	0.000699
	(0.119870)	(0.112242)	(0.004715)	(0.199614)	(0.524647)	(0.256296)	(0.959649)
Soybeans_l1	-0.018980	-0.043603	0.038522	0.016390	0.006931	0.057231	-0.006917
	(0.247528)	(0.017648)	(0.008843)	(0.473924)	(0.702872)	(0.005408)	(0.688665)
Coffee_l1	0.025981	0.000375	0.008741	-0.018511	0.011093	0.020645	-0.004715
	(0.003680)	(0.970115)	(0.275458)	(0.137730)	(0.262554)	(0.065490)	(0.616199)
Cocoa_l1	-0.001075	0.000537	-0.008615	0.004119	-0.019684	-0.020378	-0.000758
	(0.923794)	(0.965951)	(0.392328)	(0.792658)	(0.113608)	(0.147893)	(0.948866)
Sugar_l1	-0.000030	0.012280	0.000164	-0.013488	0.023385	-0.016079	-0.000576
	(0.997593)	(0.270272)	(0.985366)	(0.331059)	(0.033806)	(0.197296)	(0.956135)
Cotton_l1	0.012654	0.000537	0.035887	0.032746	0.039903	0.001428	0.061007
	(0.288298)	(0.965951)	(0.000783)	(0.048803)	(0.002497)	(0.923807)	(0.000001)
Conditional variance-covariance equation							
Const_variance	0.000004	0.000004	0.000003	0.000010	0.000001	0.000002	0.000003
	(0.180312)	(0.000037)	(0.554334)	(0.000000)	(0.002192)	(0.000145)	(0.011884)
ARCH_1	0.082725	0.036575	0.062549	0.042277	0.024828	0.034967	0.038806
	(0.000029)	(0.000000)	(0.054793)	(0.000000)	(0.000000)	(0.000000)	(0.000000)
GARCH_1	0.909160	0.951332	0.927097	0.941378	0.971951	0.961981	0.951759
	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)
DCC estimation of scalers α and β							
DCCα	0.004440						
	(0.000000)						
DCCβ	0.991278						
	(0.000000)						
Ljunk-Box test for autocorrelation (Null hypothesis: no autocorrelation in squared standardized residuals)							
LB(6)	7.427	9.036	7.608	11.38	7.6863	18.177	6.15
	(0.2831)	(0.1715)	(0.2683)	(0.077)	(0.262)	(0.0058)	(0.406)
LB(14)	16.046	16.822	20.479	15.801	25.231	34.093	9.747
	(0.3106)	(0.2658)	(0.1158)	(0.3257)	(0.03236)	(0.00199)	(0.78)
Lagrange multiplier (LM) test for presence of ARCH (Null hypothesis: no ARCH effects in standardized residuals)							
LM(6)	1.9581	29.821	3.9264	21.349	15.457	18.221	0.6873
	(0.9235)	(0.00004)	(0.6866)	(0.00158)	(0.01698)	(0.0057)	(0.9948)
LM(14)	4.956	32.407	14.848	32.557	18.044	20.843	2.4267
	(0.9864)	(0.0035)	(0.3886)	(0.0033)	(0.2048)	(0.1057)	(0.9997)
Hosking Multivariate Portmanteau test for cross-correlation (Null hypothesis: no cross-correlation in standardized squared residuals)							
HM(6)	283.9648						
	(0.652127)						
HM(14)	718.935						
	(0.185862)						
X2 tests: Rt=R	16.27						
	(0.00000)						

Note: The information criteria AIC and SIC are used to select the optimal lag orders. DCC-GARCH estimation assumes Student-t copula. P-values reported in parentheses.

Figure 3 illustrates the evolution of the estimated conditional correlation between each staple food and cash crop price return series. The figure shows some common patterns across the various pairs. First, the estimated conditional correlations display high volatility throughout the sample period. The correlation between staple food and cash return pairs are generally positive but relatively low with occasional spikes (e.g. 2009 and 2011). Second, the conditional correlation values begin to rise in 2004 to reach a peak in 2009, before falling and spiking back again around 2011. In most cases, following 2011, the conditional correlation values fall steadily to their pre-2004 levels. These correlation values are mostly driven by the dynamic correlation specification, as described in equation 4. When the conditional correlation between any pairs increases positively, it implies that the standardized residuals have the same sign and that the value of one of the residuals, or both, is getting larger. Larger values for standardized residuals means greater volatility (see equation 2). For instance, during 2004-2009, the positive increase in the conditional correlations is attributed to a rise in the conditional variance of both cash and staples commodity groups.

As illustrated by figure 3, the correlation between cash crop and staple food goes through varying correlation regimes but remains for the most part positive. The initial increase of the correlation values, which begins in 2004, coincides with the rise in world demand for commodities, mostly driven by a robust economic growth in the emerging markets. It also coincides with the surge in international food futures prices to historical levels 2007-2008. The subsequent fall in correlations observed in 2009 concurs with the period of the global financial crisis, when asset prices collapsed across the board. On the other hand, the 2011 spike displayed by the correlation pairs corresponds to the upturn in international cereal prices. The hike in these quotations was on the back of reduced supply availabilities in major producing countries, notably in the Russian Federation, the EU, and the United States, following severe droughts (e.g. United States) that affected crop yields. In addition, the Russian Federation imposed export restrictions on cereals to contain domestic price inflation.

Figure 3: Dynamic conditional correlations between staple foods and cash crops



Note: The solid grey line represents the estimated constant conditional correlation as developed by (Bollerslev, 1990).

While the results display some common patterns across crop markets, they also present some specific characteristics. We begin by looking at the evolution of the conditional correlations between maize and the cash crops. As shown in Fig 3, the correlations are highly volatile and fluctuate within a relatively large band. The correlations have mostly low values, with cotton on average displaying the largest correlation followed by sugar. The correlations values start to rise in 2004 for each of the maize and cash crop pairs, reaching a peak in 2009, before falling to pre-2004 levels. The highest value for the 2009 peak is recorded by cotton (0.31) followed by sugar, while the lowest is found for cocoa (0.23). The correlations rise again to reach a peak in 2011, when the largest value is recorded for sugar (0.26) followed by cotton (0.25), before declining to values similar to those of pre-2004 levels. Note that the conditional correlations present positive values for most of our sample period, with occasional negative values in the case of sugar (1990s), coffee, and cotton.

The level of interdependence between wheat and each of the cash crops shares resembling characteristics with that of maize. First, the dynamic correlations are quite volatile, with the exception of wheat and coffee which seems to fluctuate broadly around a narrower band. Also, the correlations are positive throughout the sample period, with only coffee presenting a negative correlation value with wheat in the mid-1990s. The conditional correlations associated with wheat also trend upward starting in 2004, culminating in 2009, before reversing back to levels pre-2004. In the case of sugar, cotton, and to a lesser extent coffee and cocoa, a short-lived spike occurs in 2011. In 2009, the highest correlation value is estimated for wheat-cotton (0.32) followed by wheat-sugar (0.28), while in the 2011 peak the highest correlation value is recorded for cotton (0.25) ahead of sugar (0.22). Similarly, the estimated conditional correlations for the pairs of soybeans-cash crops display high volatility, with a rising relationship starting in 2004. The correlation values reach a peak in 2009, before dipping back to average levels estimated for the pre-2004 period. There is also a marked surge in the correlation in 2011, in line with what is found for maize and wheat. We note that the estimated correlations are generally positive, with the exception of coffee and cocoa with some occasional negative values. For comparison purposes, we also estimate conditional correlations for the pairs of staple foods. The conditional correlations are positive, volatile, and relatively elevated. For the maize-wheat pair, there is a marked shift in the correlation level at beginning of 2000, when the level of the relationship increases to a new plateau. This coincides with the first expansion of the maize-based ethanol production in the United States. Also, as opposed to the cash crop case, there is no steady upward trend in the correlation beginning in

2004. The conditional correlation reaches a peak in 2011, declining shortly after but then rising back to 2010 levels. For the maize-soybeans and wheat-soybeans pairs, the estimated correlations present peaks for both 2009 and 2011.

After 2009, and excluding the 2011 peak, the estimated correlations fall steadily across the staple-cash crop pairs but remain positive. The declines in staple food futures are not matched with equivalent declines in cash crop futures which results in lower correlation values. In fact, cocoa futures remain relatively stable in the sample period following 2009, while coffee futures prices decline at a slower pace, when compared to staples. This asymmetry in the conditional correlation estimates and price behavior may reflect investors' choice to shift away from less liquid assets during period of market risks and uncertainty. It could also reflect a return of market fundamentals in shaping price movements. Overall, and as illustrated in Fig 3, the conditional correlation series seem to display a stationary behavior, when controlling for the 2009 and 2011 spikes. We test for stationarity in the correlation values using the Phillips-Perron (PP) test, which is robust to structural breaks and outliers. For the majority of the cases, the null hypothesis of non-stationary is rejected at the 5 percent level. This means that the interaction between cash and staple food futures prices is positive and mean reverting over the sample period.

4.2 *Results of the volatility spillover index approach*

Figure 4 illustrates the resulting net pairwise volatility spillovers using equation (9). These spillovers are obtained based on a 10-day-ahead volatility forecast errors. Overall, the net spillovers are generally negative, suggesting that the volatility runs from the staple food to the cash markets. The spillovers are also found broadly larger during the recent period of the soaring commodity prices and the global financial crisis (2007-2012), in line with the DCC-GARCH results. Note that it is the higher estimates of the cross-market coefficients of the Vector Moving Average (VMA) model that underlines the increase in the spillover indices. Large cross-market coefficients reflect greater unpredictability in the staple food markets, which eventually transmits to cash crop markets.

In the case of maize, the spillovers are largely negative in comparison to cash crops, suggesting volatility transmission running from maize to cash crops. This is particularly marked for cocoa, coffee, and cotton. Despite being a net receiver of volatility from maize, particularly during the period of soaring commodity prices, sugar does transmit some shocks to the maize market more so than the other cash crops, reflecting potentially the linkage with the energy sub-sector through the biofuel complex. Volatility transmission from maize is also significant during the financial crisis. Similar observations can be made for both soybeans and wheat, which are found to be net transmitters of shocks to cash futures prices, particularly during 2007-2012.

Table 4 and 5 illustrate the average results summarized in terms of volatility spillover matrix for the full sample and a restricted sample, respectively. The restricted sample covering 2007-2012, corresponds to the period when conditional correlation values are positive and increasing. The total (non-directional) volatility spillover for the full sample, appearing in the lower right corner of table 4, amounts to about 20 percent. This means that 20 percent of the volatility forecast error variance of the VMA system is due to volatility spillover among the 7 markets. The bulk of the forecast error variance for each of the variables is due to their own innovations. Results also show 18 percent of the forecast error variance of cash crop markets is explained by spillover effects from the staple food markets (directional spillover), while 12.8 percent of the forecast error variance of the staple food is explained by innovations in cash crop markets.

Table 4 Volatility spillover matrix full sample (1990-2016)

	maize	*wheat*	*soybeans*	*coffee*	*cocoa*	*cotton*	*sugar*	*spillover*
maize	0.6029	0.1814	0.1783	0.0065	0.0055	0.0160	0.0095	*0.3971*
wheat	0.2017	0.6697	0.0902	0.0072	0.0040	0.0160	0.0112	*0.3303*
soybeans	0.1961	0.0895	0.6621	0.0077	0.0077	0.0242	0.0125	*0.3379*
coffee	0.0093	0.0107	0.0112	0.9260	0.0216	0.0061	0.0152	*0.0740*
cocoa	0.0099	0.0059	0.0117	0.0220	0.9273	0.0110	0.0122	*0.0727*
cotton	0.0236	0.0212	0.0315	0.0052	0.0088	0.8981	0.0117	*0.1019*
sugar	0.0148	0.0152	0.0187	0.0154	0.0111	0.0119	0.9130	*0.0870*
							Total spillover %:	*20.014*

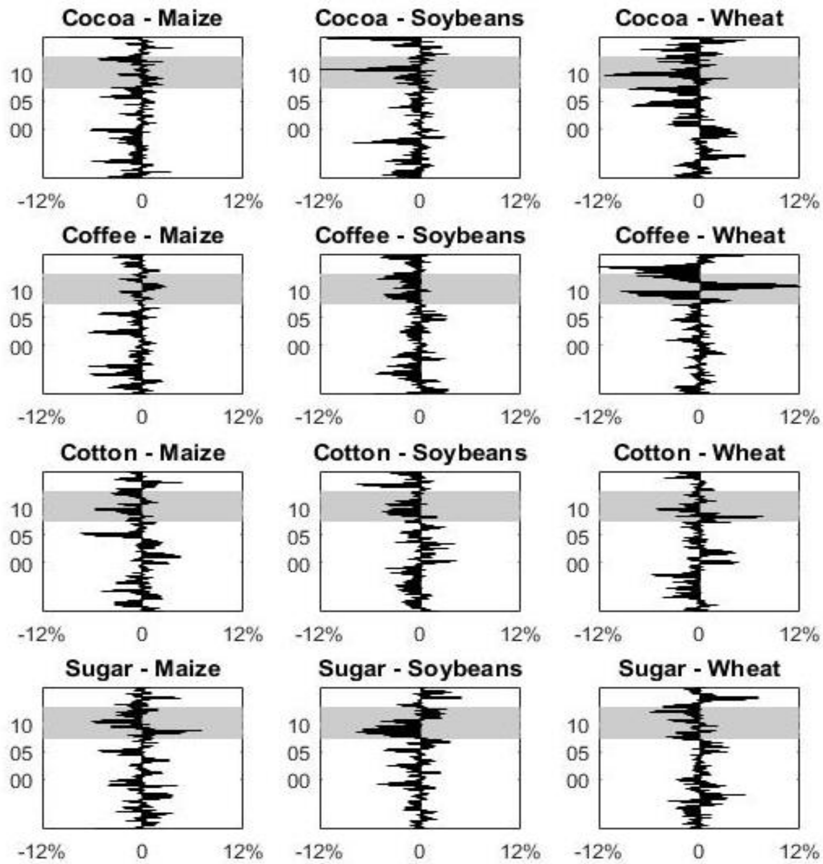
Notes: the ijth entry of the volatility spillover matrix corresponds to the contribution to the forecast error variance of crop i coming from shocks to crop j. The diagonal elements are the own contributions.

Table 5 Volatility spillover (2007-2012)

	maize	*wheat*	*soybeans*	*coffee*	*cocoa*	*cotton*	*sugar*	*spillover*
maize	0.4745	0.2118	0.1820	0.0371	0.0174	0.0408	0.0364	*0.5255*
wheat	0.2291	0.5121	0.1317	0.0397	0.0166	0.0396	0.0313	*0.4879*
soybeans	0.1935	0.1299	0.5056	0.0483	0.0281	0.0558	0.0388	*0.4944*
coffee	0.0527	0.0534	0.0647	0.6626	0.0500	0.0501	0.0665	*0.3374*
cocoa	0.0341	0.0275	0.0449	0.0601	0.7634	0.0363	0.0339	*0.2366*
cotton	0.0583	0.0522	0.0746	0.0501	0.0266	0.6942	0.0441	*0.3058*
sugar	0.0533	0.0436	0.0548	0.0707	0.0304	0.0449	0.7023	*0.2977*
							Total spillover %:	38.362

Notes: the ijth entry of the volatility spillover matrix corresponds to the contribution to the forecast error variance of crop i coming from shocks to crop j. The diagonal elements are the own contributions.

Figure 4: Net pairwise volatility spillovers food and cash crops



Note: grey bar is period of food price spikes, 07/07-12/12.

When we restrict the sample to 2007-2012 (table 5), the bulk of the contribution to the variance of the forecast errors is still due to own innovations, but the size of those contributions are lower in comparison to the estimation with the full sample (table 4). Lower own shocks are now balanced with higher spillover effects. Total (non-directional) volatility spillover, appearing in the lower right corner, show that 38 percent of the forecast error variance of the seven-dimensional VMA system is due to volatility spillovers among the selected variables. The contribution of volatility spillovers to the forecast error variance is almost double its size under the full sample estimation, suggesting higher volatility interdependence, in line with the results obtained with the DCC-GARCH model.

Results also show that 61.4 percent of the forecast error variance of cash crop series is explained by spillover effects from the staple food markets, while about 43 percent of the forecast error variance of staple foods is explained by innovations in cash crops. This illustrates the significant impact that staple foods have on the cash crops. Shocks in staple food markets contribute 18.5 percent to the forecast error variance of cotton, while they contribute about 17 percent and 15 percent to forecast error variance of coffee and sugar, respectively.

A question that emerges is whether a change in the calculated spillover index implies a change in the DCC-based estimated conditional correlation. For illustrative purposes, consider the pair maize-sugar, so that the variance of the h-step forecast error for sugar is expressed as:

$$\mathrm{var}(\mathrm{y}_{\mathrm{su,T+h}} - y_{su,T+h|T}) = \sigma_{su}^2 \sum_{s=0}^{h-1} (\theta_{susu}^s)^2 + \sigma_{mz}^2 \sum_{s=0}^{h-1} (\theta_{sumz}^s)^2 \qquad (11)$$

where, su refers to sugar, mz to maize, $\sigma_{su}^2 = \mathrm{var}(su_t)$, $\sigma_{mz}^2 = \mathrm{var}(mz_t)$, θ_{susu}^s is the VMA own-market coefficient, θ_{sumz}^s is the VMA cross-market coefficient, and h is the number of step-ahead forecasts. Similarly, the variance of the h-step forecast error for maize may be expressed as:

$$\mathrm{var}(\mathrm{y}_{\mathrm{mz,T+h}} - y_{mz,T+h|T}) = \sigma_{mz}^2 \sum_{s=0}^{h-1} (\theta_{mzmz}^s)^2 + \sigma_{su}^2 \sum_{s=0}^{h-1} (\theta_{mzsu}^s)^2 \qquad (12)$$

We recall that the estimated conditional correlation is basically driven by the conditional covariance as expressed in equation (4): $\mathrm{Q_t} = (1 - \alpha - \beta)\overline{\mathrm{Q}} + \alpha u_{\mathrm{t-1}} u'_{\mathrm{t-1}} + \beta \mathrm{Q_{t-1}}$, which in the case of the maize-sugar pair can be specified as:

$$\mathrm{q_{mzsu,t}} = (1 - \alpha - \beta)\overline{\mathrm{Q}} + \alpha(u_{\mathrm{mz,t-1}} u_{\mathrm{su,t-1}}) + \beta \mathrm{q_{mzsu,t-1}}$$

A change in the spillovers going from maize to sugar means that the value obtained by $\sigma_{mz}^2 \sum_{s=0}^{h-1} (\theta_{sumz}^s)^2$ is altered. That can be caused by a change in σ_{mz}^2 and/or $\sum_{s=0}^{h-1} (\theta_{sumz}^s)^2$. When σ_{mz}^2 changes, it means that the standardized maize residuals changes since the conditional variance depends on the standardized residuals by assumption (see equation 2) [2]. Similarly, a change in $\sum_{s=0}^{h-1}(\theta_{sumz}^{s})^2$ implies a change in the standardized errors, which modifies $\mathrm{Q_t}$. Hence, ceteris paribus, a change in the DCC-based conditional correlations for the maize-sugar pair can be driven by a change in spillover $\sigma_{mz}^2 \sum_{s=0}^{h-1}(\theta_{sumz}^{s})^2$ and/or a change in own volatility $\sigma_{su}^2 \sum_{s=0}^{h-1}(\theta_{susu}^{s})^2$. The direction of the change depends on whether the product of the standardized residuals $u_{\mathrm{mz,t-1}}u_{\mathrm{su,t-1}}$, in equation 4, is positive or negative. As a matter of illustration, the interaction between the estimated DCC conditional correlations and the net spillover indices for the maize-sugar pair in normalized form is presented in figure A1. The upward trend in the conditional correlation from about 2004 to 2011 is influenced by shocks originating from both markets, with a marked net-volatility transmission from sugar to maize in 2008 (positive peak), while maize transmitting large shocks for most of the period with a pronounced peak in mid-2010 (negative peak). Figure A2 shows the evolution of the estimated conditional variances of maize and sugar, highlighting the large peak of volatility in maize in mid-2010, which far outweigh the conditional volatility in sugar.

5 Conclusion

The analysis in this paper examines the interdependence and the dynamics underlying staple food and cash crop international futures prices. Understanding the price dynamics between these commodity groups is particularly important for

[2] Note that since the GFEVDs are based on price ranges, and the conditional covariance, as expressed in equation (4), are based on price returns, the conditional variance of the range need to correlate with the conditional variance of the return for the standardized errors, in equation 4, to change. In the case of wheat, for example, the correlation between the conditional variance of the range and the conditional variance of the return is found to be 0.79, with an OLS estimation yielding a highly significant coefficient at the 1 percent level for the conditional variance of the range entered as the explanatory variable.

the developing countries that rely on food imports and earnings from cash crop exports to meet food security objectives. We use a multivariate Copula-DCC-GARCH framework and spillover indices approach based on FEVDs to explore the international price dynamics. While the unconditional correlation between staples and cash markets is relatively low, results from the estimation highlight the volatile nature of the conditional correlations across markets, with the correlations being greater in 2007-2012, corresponding to the period of high commodity prices and financial market stress. Increasingly, commodities are considered as investment assets very much like equity and bond holdings, which may explain the correlation in the short-run between seemingly unrelated futures price series such as wheat and cocoa. There is generally little substitution in supply and demand between cash and food crops in the physical market, so the substitution principle is unlikely to explain the price co-movement. Aside from macroeconomic factors, changes in factor input costs could be responsible for some level of co-movement in the long-run. The volatility spillover analysis based on rolling generalized FEVDs indicates that transmission is generally asymmetric running mostly from food staple futures to cash crop futures prices, suggesting, that the information transmission takes place from the staple food to the cash crop markets. The direction of information may in fact reflect the relatively greater liquidity in the staple food markets.

There are few policy implications than can be drawn from this analysis. First, for net food importing developing countries that specialize in cash crop exports, when international food prices increase, it is likely that their cash crop export earnings will increase as well, helping to offset some, or all, rises in the food import bill. That is because international demand for cash crops is inelastic (FAO, 2004), so the change in export volume (due to lower demand) is smaller than the change in export prices, leading to higher export earnings. Hence cash crop production and export can limit the negative effects of high food import prices. Second, cash crop exporting countries that engage in hedging through futures markets should consider movements in staples futures prices as well. With staples and cash crop prices moving together, knowing, for instance, that the market expects futures prices of staples to rise can allow cash crop exporting countries to consider reducing the volume of hedged crops, and hence save on costs linked with futures market transactions.

Third, assuming that international prices transmit to domestic markets, the fact that cash crop and staples prices are correlated means that crop diversification at the smallholder farm level is unlikely to lower price risks. On the contrary, smallholders holding a comparative advantage in the production of cash crops may be better off specializing in these crops and using the earnings to buy food at the local market. This is provided that local markets function adequately, in the sense that they are well integrated with national and regional markets. Reality on the ground shows, however, that smallholders still devote a considerable share of their resources to food, and livestock, production, despite holding a comparative advantage in cash crop production. This outcome results from the need to mitigate risks associated with the perennial nature of cash crops as well as losses that often emerge from the prevalence of pests, diseases, and extreme weather events, which affect smallholders' revenue. Therefore, in order to exploit fully the gains from cash crop specialization, public policies that aim at facilitating access to factor inputs, including pest and disease resistant crop varieties, technology, knowledge, as well as access to credit market can help alleviate production risks. Ultimately, these policies generate the necessary incentives needed to exploit any existing comparative advantage in cash crop production. Finally, because of the correlation in the prices, there is some scope for Governments to introduce support measures targeted at smallholder cash crop producers, when food prices are on the rise and expected to remain so for some time, and to lessen these measures progressively as cash crop prices begin to increase.

Future research should proceed on several fronts. First, there is a necessity for more research into the theoretical and empirical estimation of higher dimension MGARCH models that estimate spillover parameters. Most studies use a general form of BEKK-GARCH specification for that purpose. Generally, these models do not exceed a trivariate specification, given the prevailing convergence issues, especially when exogenous variables are added in the mean and/or variance equations. As opposed to a DCC-GARCH specification, a BEKK model enables the full use of information contained in the dynamic interaction among a system of variables, as it is the case with high dimension VAR systems. In addition to the convergence issues, there is considerable knowledge gap into the statistical and asymptotic properties of higher dimension BEKK-MGARCH. Second, further research is needed to explore the theoretical linkages between the own and volatility spillover GARCH-based estimates and those obtained from volatility indices based on the forecast error variance decompositions. As we saw in this paper, there is scope for interaction between both methods. Finally, since our study on the interaction effects between staple and food futures prices is conducted at a global level, the next natural step is to verify whether the integration holds at the country level as well.

References

Aepli, M.D., Füss, R., Henriksen, T.E.S., and F. Paraschiv (2017): Modeling the multivariate dynamic dependence structure of commodity futures portfolios. *Journal of commodity Markets* (6): 66–87.

Al-Maadid, A., Caporale, G.M., Spagnolo, F., and N. Spagnolo (2017): Spillovers between food and energy prices and structural breaks. *International Economics* (150): 1–18.

Bartram, S.M., Taylor, S.J., and Y.-H. Wang (2007): The Euro and European financial market dependence. *Journal of Banking and Finance* 31(5): 1461–1481.

Bicchetti, D. and N. Maystre (2013): The synchronized and long-lasting structural change on commodity markets: Evidence from high frequency data. *Algorithmic Finance* (2): 233–239.

Bollerslev, T. (1990): Modelling the Coherence in Short-Run Nominal Exchange Rates: A Multivariate Generalized Arch Model. *The review of Economics and Statistics* 72(3): 498–505.

Breymann, W., Dias, A., and P. Embrechts (2003): Dependence structures for multivariate high-frequency data in finance. *Quantitative Finance* 3(1): 1–14.

Celık, S. (2012): The more contagion effect on emerging markets: The evidence of DCC-GARCH model. *Economic Modeling* 29(5): 1946–1959.

Chang, T.-H. and H.-M Su (2010): The substitutive effect of biofuels on fossil fuels in the lower and higher crude oil price periods. *Energy* 35(7): 2807–2813.

Chiang, T.C., Jeon, B.N., and H. Li (2007): Dynamic correlation analysis of financial contagion: Evidence from Asian markets. *Journal of International Money and Finance* 26(7): 1206–1228.

Deaton, A. and G. Laroque (1992): On the Behaviour of Commodity Prices. *The Review of Economic Studies* 59(1): 1–23.

Demarta, S. and A.J. McNeil (2005): The t Copula and Related Copulas. *International Statistical Review* 73(1): 111–129.

Diebold, F.X. and K. Yilmaz (2012): Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting* 28(1): 57–66.

Diebold, F.X. and K.Yilmaz (2009): Measuring Financial Asset Return and Volatility Spillovers, with Application to Global Equity Markets. *The Economic Journal* 119(534): 158–171.

Engle, R. (2002): Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models. *Journal of business and Economic Statistics* 20(3): 339–350.

Food and Agriculture Organization (FAO) (2004): Commodity Market Review 2003-2004. Commodities and Trade Division.

Fattouh, B., Kilian, L., and L. Mahadeva (2012): The Role of Speculation in Oil Markets: What Have We Learned so Far? (SSRN Scholarly Paper No. ID 2034134). Social Science Research Network, Rochester, NY.

Gao, L. and L. Liu (2014): The Volatility Behavior and Dependence Structure of Commodity Futures and Stocks. *Journal of Futures Markets* 34(1): 93–101.

Gardebroek, C. and M.A. Hernandez (2013): Do energy prices stimulate food price volatility? Examining volatility transmission between US oil, ethanol and corn markets. *Energy Economics* (40): 119–129.

Ghalanos, A. (2015): Package rmgarch: Multivariate GARCH Models. R package version 1.3-0, https://cran.r-project.org/web/packages/rmgarch/

Gilbert, C.L. (2010): How to Understand High Food Prices. *Journal of Agricultural Economics* 61(2): 398–425.

Govereh, J. and T.S Jayne (2003): Cash cropping and food crop productivity: synergies or trade-offs? *Agricultural Economics* 28(1): 39–50.

Grosche, S.-C. and T. Heckelei (2016): Directional Volatility Spillovers Between Agricultural, Crude Oil, Real Estate, and Other Financial Markets, in: Food Price Volatility and Its Implications for Food Security and Policy. Springer, Cham, pp. 183–205.

Hamilton, J.D. and J.C. Wu (2015): Effects of Index-Fund Investing on Commodity Futures Prices. *International Economic Review* 56(1): 187–205.

Harri, A. and D.Hudson (2009): Mean and variance dynamics between agricultural commodity prices and crude oil prices, in: Presentation at the Economics of Alternative Energy Sources and Globalization: The Road Ahead Meeting, Orlando, FL. pp. 15–17.

Headey, D. and D. Fan. (2008): Anatomy of a crisis: The causes and consequences of surging food prices (IFPRI discussion paper No. 831). International Food Policy Research Institute (IFPRI).

Irwin, S.H. and D.R. Sanders (2011): Index Funds, Financialization, and Commodity Futures Markets. *Applied Economic Perspectives and Policy* 33(1): 1–31.

Ji, Q. and Y. Fan (2012): How does oil price volatility affect non-energy commodity markets? Applied Energy 89(1): 273–280.

Jondeau, E. and M. Rockinger (2006): The Copula-GARCH model of conditional dependencies: An international stock market application. *Journal of International Money and Finance* 25(5): 827–853.

Kim, J.-M. and H. Jung (2016): Linear time-varying regression with Copula–DCC–GARCH models for volatility. *Economic Letters* (145): 262–265.

Koop, G., Pesaran, M.H., and S.M Potter (1996): Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics* 74(1): 119–147.

Ling, S. and M. McAleer (2003): Asymptotic Theory for a Vector ARMA-GARCH Model. *Econometric Theory* 19(2): 280–310.

Lombardi, M.J. and F. Ravazzolo (2016): On the correlation between commodity and equity returns: Implications for portfolio allocation. *Journal of Commodity Markets* 2(1): 45–57.

Manner, H. and O. Reznikova (2012): A Survey on Time-Varying Copulas: Specification, Simulations, and Application. *Econometric Reviews* 31(6): 654–687.

Maxwell, S. and A. Fernando (1989): Cash crops in developing countries: The issues, the facts, the policies. *World Development* 17(11): 1677–1708.

Mensi, W., Beljid, M., Boubaker, A., and S. Managi (2013): Correlations and volatility spillovers across commodity and stock markets: Linking energies, food, and gold. *Economic Modelling* (32): 15–22.

Mittal, A. (2009): The 2008 food price crisis: rethinking food security policies. *G-24 Discussion Paper series*, United Nations (UN).

Nazlioglu, S., Erdem, C., and U. Soytas (2013): Volatility spillover between oil and agricultural commodity markets. *Energy Economics* (36): 658–665.

Norton, R.D. and P.B. Hazell (1986): Mathematical programming for economic analysis in agriculture. Macmillan; London: Collier Macmillan.

Olson, E., J. Vivian, A., and M.E. Wohar (2014): The relationship between energy and equity markets: Evidence from volatility impulse response functions. *Energy Economics* (43): 297–305.

Patton, A.J. (2006): Modelling Asymmetric Exchange Rate Dependence. *International Economic Review* 47(2), 527–556.

Pesaran, H.H., and Y. Shin (1998): Generalized impulse response analysis in linear multivariate models. *Economics Letters* 58(1), 17–29.

Roy, R.P., and S. Sinha Roy (2017): Financial contagion and volatility spillover: An exploration into Indian commodity derivative market. Economic Modelling (67): 368-380.

Serra, T. (2011): Volatility spillovers between food and energy markets: A semiparametric approach. *Energy Economics* 33(6), 1155–1164.

Sklar, M. (1959): Fonctions de Répartition à N Dimensions et Leurs Marges. Publications de l'Institut de Statistique de L'Université de Paris (8): 229-231.

Tadesse, G., Algieri, B., Kalkuhl, M., and J. von Braun (2014): Drivers and triggers of international food price spikes and volatility. *Food Policy* (47): 117–128.

Theriault, V., and D.L. Tschirley (2014): How Institutions Mediate the Impact of Cash Cropping on Food Crop Intensification: An Application to Cotton in Sub-Saharan Africa. *World Development* (64): 298–310.

Timmer, C.P. (1997): Farmers and markets: The political economy of new paradigms. *American Journal of Agricultural Economics* 79(2): 621–627.

Trostle, R. (2008): Global agricultural supply and demand: factors contributing to the recent increase in food commodity prices. US Department of Agriculture, Economic Research Service Washington, DC, USA.

Trujillo-Barrera, A., Mallory, M., and P. Garcia (2012): Volatility Spillovers in U.S. Crude Oil, Ethanol, and Corn Futures Markets. *Journal of Agricultural and Resource Economics* (37)2: 247–262.

Vivian, A. and M.E. Wohar (2012): Commodity volatility breaks. *Journal of International Financial Markets, Institutions and Money* 22(2): 395–422.

Von Braun, J., and E. Kennedy (1986): Commercialization of subsistence agriculture: Income and nutritional effects in developing countries. International Food Policy Research Institute Washington.

Weber, M.T., Staatz, J.M., Crawford, E.W., Bernsten, R.H., and J.S. Holtzman (1988): Informing Food Security Decisions in Africa: Empirical Analysis and Policy Dialogue. *American Journal of Agricultural Economics* 70(5): 1044–1052.

Ye, Y. (1987): Interior Algorithms for Linear, Quadratic, and Linearly Constrained Non-Linear Programming. Ph.D Thesis. Department of EES, Stanford University, Stanford, CA.

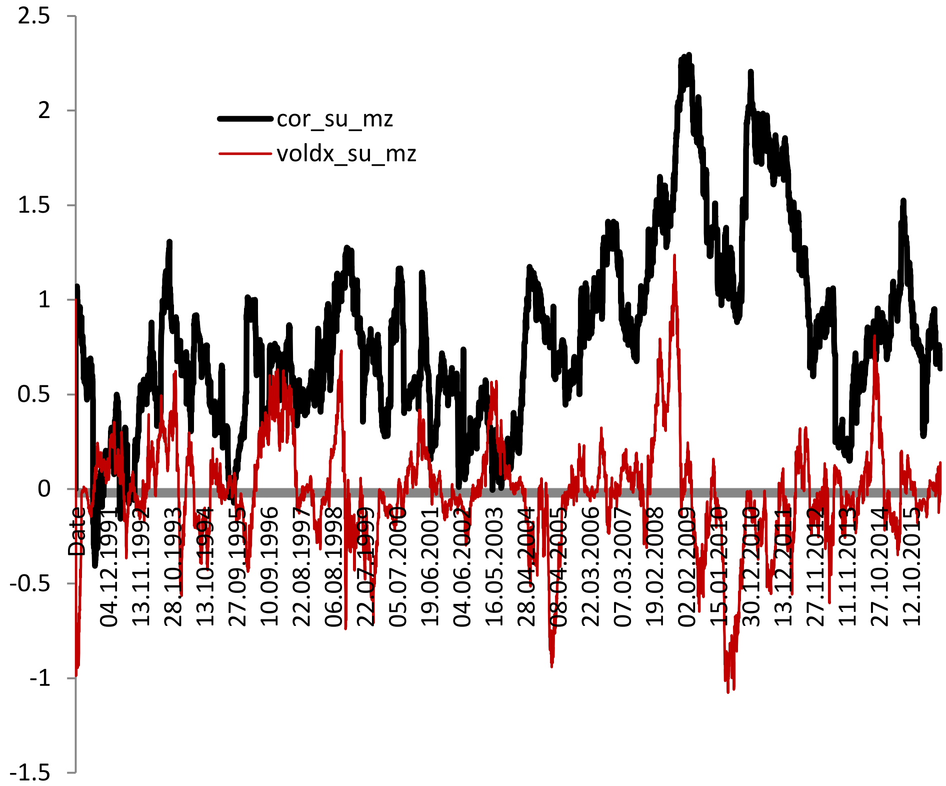
Appendix

Table A1: Unconditional correlation between cash and staple foods

	Maize	*Wheat*	*Soybeans*	*Coffee*	*Cotton*	*Cocoa*	*Sugar*
Maize	1	0,548485	0,542463	0,096827	0,162436	0,097355	0,126245
Wheat	0,548485	1	0,365902	0,103355	0,154329	0,077876	0,127676
Soybeans	0,542463	0,365902	1	0,107259	0,188592	0,108983	0,138948
Coffee	0,096827	0,103355	0,107259	1	0,077756	0,153544	0,128315
Cotton	0,162436	0,154329	0,188592	0,077756	1	0,101417	0,114111
Cocoa	0,097355	0,077876	0,108983	0,153544	0,101417	1	0,109738
Sugar	0,126245	0,127676	0,138948	0,128315	0,114111	0,109738	1

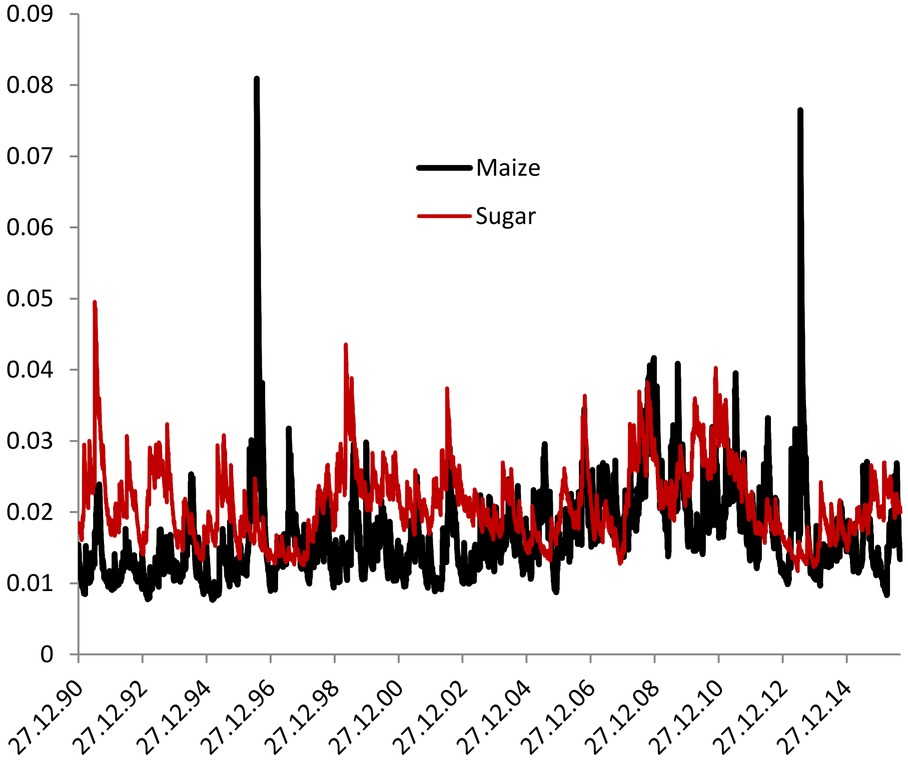
Note: all values are significant at 5 percent level.

Figure A1: Net pairwise volatility spillovers and estimated conditional correlation between food and cash crops



Note: cor_su_mz stands for dynamic conditional correlation between maize and sugar, while voldx_su_mz is the derived net pairwise volatility index between maize and sugar.

Figure A2: Evolution of maize and sugar conditional variances



Note: The conditional variances are derived by estimating a Copula-DCC-GARCH model.