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Estimating Price Volatility Transmission between World Crude Oil and Selected Food Commodities: A BEKK Approach

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ABSTRACT : This paper quantified the behaviour and extent of oil price and selected food commodity price volatilities using a multivariate-BEKK GARCH model to analyse the shocks and volatility transmission effect between crude oil and these commodities prices during 1990-2015. In line with the properties of time series data, a series of test such as collinearity, unit root as well as the presence of ARCH effects were conducted. The objective of this paper was to understand the most volatile commodity due to changes in world crude oil price returns and explore ways to reduce volatility relevant to food security and its stability for future planning purposes. The paper further used real price returns and demeans for normalization. Empirical results showed significant volatility transmission effects between crude oil and the all the food commodity except for dairy. Strong correlations existed between crude oil price returns and meat, cereal, edible oils and sugars. Shocks were also observed food commodity prices and its first lags.

Keywords: Prices, volatility, crude oil, food commodities, multivariate GARCH

Dünya Ham Petrol ve Seçilmiş Gıda Ürünlerin Arasındaki Fiyat Oynaklığın Tahmini: Bir BEKK-GARCH Yaklaşımı

ÖZET : Bu çalışma, 1990-2015 yılları arasında dünya ham petrol ve bazı temel gıda fiyatları arasındaki geçişkenliği analiz etmek amacıyla, çok değişkenli-BEKK GARCH modeli kullanarak petrol fiyatının ve seçilen gıda ürünlerin fiyat oynaklığının hareketi ve boyutunu ortaya koymayı amaçlamıştır. Bu çalışma dünya ham petrol fiyatındaki değişme ile tarımsal gıda piyasaları arasındaki fiyat oynaklığının kaynağını anlamak, oynaklığı azaltma arayışlarını artırmak, oynaklıktan gıda güvencesini kontrol altına almak ve gelecekte planlamada istikrarı sağlamak amacı büyük önem taşımaktadır. Makalede ayrıca, çalışmada gerçek (reel) fiyat getirileri uygulanmış ve seri normalleştirilmiştir. Ampirik sonuçlar, ham petrol ile mandıra ürünleri hariç diğer gıda ürünlerinin fiyat getirileri arasında belirgin bir oynaklık geçişkenliği etkisinin olduğunu göstermiştir. Ham petrol fiyatı getirisi ile et, tahıl, yenilebilir yağlar ve şekerler arasında kuvvetli ikili çapraz korelasyon ilişkisi mevcuttur. Ayrıca şoklar gıda ürünlerin fiyatlarında ve ilk gecikmelerinde gözlenmiştir.

Anahtar kelimeler*:* Fiyatlar, oynaklık, ham petrol, gıda ürünleri, çok değişkenli GARCH

INTRODUCTION

The current global food insecurity can partly be blamed on price fluctuations between current energy demands and food commodities in the world market. The fundamental cause of these fluctuations is the volatility of oil prices in the world market. According to the FAO (2011), volatility refers to the variations in economic variables over a time period. According to Busse et al. (2011), there is an increasing positive correlation between energy prices and agricultural commodities, particularly during the 2006-2008 period. This correlation not only increases during periods of high prices, but also keeps rising over time. The major threat to food security and economic-well-being in various countries is the increasing food prices and volatilities where high proportion of household incomes goes to food spending (Prakash, 2011).

Whilst the debate is on the level of price volatility transmission, the extent of the spillover effect of these volatility transmission needs to be assessed. Based on the conditions of non-linear models, time series properties such as non-stationarity and co-movements (tendency to move together with time) are required to determine the suitability of data for analysis. Engle and Granger (1987) introduced the theory of co-integration and error-correction frameworks used for nonlinear models which characterizes nature of non-stationarity and co-movements. Garcia-German et al. (2015) evaluated price transmission between global agricultural markets and consumer food price indices in the European Union (EU) using error correction models due to the presence of cointegration among variables. This was to observe the extent and speed at which agricultural price movements influences consumer food prices. Due to level of economic variables such as price fluctuations resulting in volatility in other sectors, there has been increased interest in analyzing the behavior of macroeconomic variables which are nonlinear in nature. The most popular non-linear models used are the Autoregressive Conditional Heteroscedastic (ARCH) models by Engle (1982) and the Generalized Autoregressive Conditional Heteroscedastic (GARCH) models Bollerslev (1986). Relevant to this analysis is the multivariate GARCH model specifically the BEKK and the DVECH approach because GARCH models treats heteroscedasticity as a variance that can be modeled and predicted (Engle, 2001).

Nazlioglu *et al*. (2012) in a similar work, grouped data into pre and post crisis to analyse volatility transmission between oil and agricultural commodity markets (wheat, corn, soybeans and sugar) but applied variance causality test proposed by Hafner and Herwartz (2006). Results showed volatility spillovers from oil market to the agricultural markets except for sugar. Sattary et al (2014) also applied DVECH approach to observe volatility spillover between world oil prices and sectors of stock market of Istanbul (namely Borsa Istanbul, BIST) and results showed an interaction between oil returns and the underlying markets in terms of both shocks and conditional variance.

Serra (2015) recently focused on monthly time series data to assess the relevance of time-factor in volatility analysis in the short run with the assumption that long-run patterns are constant in risk uncertainty contrary to the current study in which we use the long run approach. Short-run and long-run introduce time-factor characterized by time series data and required for both ARCH and GARCH analysis. This time varying data are known to violate many assumptions underlying conventional econometric models that could result in completely spurious results. Li and Majerowska, (2008), used a four-variable asymmetric BEKK-GARCH approach and found evidence of shock returns and volatility spillovers from developed to emerging markets in Warsaw and Budapest and the established markets in Frankfurt and the U.S. Their findings realized an estimated time-varying conditional covariance and variance decompositions indicating a limited interaction among the markets. Based on this review on volatility transmission and spillover effects between commodities, this analysis adopted the BEKK approach proposed by Engle and Kroner (1995) to identify the extent and source of shock and volatility transmissions from world crude oil prices returns and the demeans of the food commodity price indices. The multivariate GARCH approach examined returns and volatility linkages and responses in cross-sector volatility spillover effects and asymmetric properties.

The key question answered in this research was whether or not world crude oil price returns volatility is really transmitted to world's food commodity consumer price indices. This analysis observed the trend, behaviour and extent of crude oil price volatility transmission to the selected food commodities and also the most affected commodity. This paper further adopted the demean approach using differences in real returns for each corresponding commodity. Also, we applied the BEKK parameterization of MGARCH models which does not impose restrictions of constant correlation between variables in the long run. BEKK further addressed the positive definiteness of VECH similar to Ewing and Malik (2005) use of BEKK-MGARCH model parameterization for volatility transmission. Hence, this analysis captured the fundamental volatility dynamics while still retaining the virtue of being very parsimonious in nature.

MATERIALS AND METHODS

Nominal monthly consumer price indices from January, 1990 to September, 2015 for the world meat, dairy, cereal, edible oil, sugar and general foods was obtained from the World Bank. These consumer price indices were deflated. We then computed the returns on the price indices (for the food commodities including general food) and real prices (for the crude oil) as:

$$R_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}} \qquad (1).$$

The first step in the study was to observe the general characteristics of most price time series data. These characteristics include the presence of a unit root, tendency of prices of related markets to co-move, that is, co-movements can result from the presence of an equilibrium relationship between individual price series known as co-integration. Commodity prices often exhibit volatility that tends to change over time and thus displays a clustering behaviour. This paper specified the mean equation for each return series which is the first step in multivariate GARCH models as:

$$R_{it} = \mu_i + \alpha R_{i,t-1} + \varepsilon_{it} \qquad (2).$$

where R_{it} is the return on series i between time t and t−1, μ_i is a long-term drift coefficient for commodity in question, and ε_{it} is error term for the return on series i at time t. Keeping in line with the literature on ARCH-class models, Eq. (1) was estimated and the residuals examined the presence of ARCH effects using the test described by Engle (1982). Results of each estimated series showed evidence of ARCH effects. We further applied the variant of the multivariate GARCH model which detects volatility transmission between different series including the persistence of volatility within each series. For this reason, the BEKK parameterization was used for the bivariate GARCH proposed by Engle and Kroner (1995).

Abdelradi and Serra (2014) realized that the multivariate BEKK-GARCH model is also an improvement over other more restrictive specifications which are unable to capture asymmetric volatility patterns. This analysis similar to Kroner and Ng (1998) who used an asymmetric specification of the multivariate BEKK-GARCH model. To ensure covariance matrix are positive semi-definite for non-negativity of estimated variances and asymmetries, we included a quadratic function similar to Malik and Ewing (2009), Sattary et al. (2014), Abdelradi and Serra (2014) for parameterization in GARCH (1, 1) given by:

$$H_t = CC' + A'\mu_{t-1}A + B'\mathrm{H}_{t-1}\mathrm{B} \qquad (3).$$

Where H_t is the (n x n) variance-covariance matrix, A, B, and C represents (n x n) parameter matrices.

We further maximized the likelihood function assuming that the error term is normally distributed.

$$L(\theta) = -\mathrm{T}\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}(\ln|Ht| + \varepsilon'_t \mathrm{H}^{-1}\varepsilon_t) \quad (4).$$

Where θ is the parameter vector to be estimated and T is the number of observations. Several iterations were performed using simplex algorithms recommended by Engle and Kroner (1995). BFGS estimation was used to obtain the final estimates of variance-covariance with the corresponding standard errors in RATS 9.1 statistical software.

RESULTS AND DISCUSSIONS

Results from the analysis showed a level of co-integration and a tendency for the price (crude oil) and price indices to co-move as a result of an equilibrium relationship between individual price series known as co-integration. Residuals showed appropriateness of ARCH effects. This is shown in the descriptive statistics in Table 1 below. As a result of the presence of ARCH effects and in line with time series data, the mean equation for each of the series was estimated. Based on the values of the Ljung-Box statistic for the six price returns, significant autocorrelation was detected. Consumer price indices for edible oil, sugar and crude oil price returns showed high standard deviations of 4.194, 6.706 and 6.81, respectively explaining the high volatility of edible oil and sugar in the beverage and confectionary industry.

Table 1: Descriptive Statistics

Descriptive Statisitcs	**Meat (i=1)**	**Dairy (i=2)**	**Cereal (i=3)**	**Edible Oil (i=4)**	**Sugar (i=5)**	**Crude Oil (i=7)**
Mean	0.016	0.017	0.005	0.081	-0.175	0.035
Std. Dev	2.617	3.942	2.870	4.194	6.706	6.811
Skewness	0.092	-0.300	0.075	-0.106	0.198	4.252
Kurtosis	-0.072	4.652	0.760	1.421	0.695	63.476
Jarque-Bera	0.500	282.301	7.701	26.492	8.219	52635.839
Prob.	0.000	0.000	0.000	0.000	0.000	0.000

Note: The total number of observations is 308 with a multivariate Q(12) of 436.763. Chi-Square statistic was 0.427 with a Multivariate ARCH test of 3291.

Parameter Estimates for mean function

Table 2 below shows the various parameters for the mean estimates for consumer price indices returns on meat, dairy, cereal, edible oil, sugar and crude oil price returns. Results showed significant interaction between the individual commodities with its lags at 1%, 5% and 10% respectively. Also, a 1% level of significance was observed between meat and lagged general price indices with a positive *a priori* expectation. Various shocks were observed and hence having effects on each other.

Table 2: Mean parameter estimates for shocks

Estimate	Meat (i=1)	Dairy (i=2)	Cereal (i=3)	Edible Oil (i=4)	Sugar (i=5)	Crude Oil (i=6)
$\varepsilon^2_{1,t}$	0.3309*** (10.787)	0.0190 (1.519)	0.0095 (1.373)	0.0052 (0.535)	0.1163* (1.840)	0.0195 (0.388)
$\varepsilon_{1,t}\varepsilon_{2,t}$	0.0071 (0.211)	-0.1151** (-2.978)	0.0163* (2.006)	0.0111 (0.768)	0.1094* (1.700)	-0.0045 (-0.207)
$\varepsilon_{1,t}\varepsilon_{3,t}$	0.1237*** (3.882)	-0.0423* (-2.368)	0.0482** (2.861)	0.0208 (0.881)	0.4671** (3.23)	-0.0258 (-0.9142)
$\varepsilon_{1,t}\varepsilon_{4,t}$	0.0598* (2.051)	-0.0259* (-2.010)	-0.0107 (-1.356)	0.0719 (1.031)	0.0763 (1.283)	-0.0228 (-0.860)
$\varepsilon_{1,t}\varepsilon_{5,t}$	0.0889*** (4.990)	0.0055 (0.947)	-0.0031 (-0.686)	-0.0045 (-0.718)	0.3435*** (3.426)	0.0076 (0.314)
$\varepsilon_{1,t}\varepsilon_{6,t}$	-0.0157 (-0.985)	-0.0130 (-1.566)	-0.0035 (-0.875)	0.0023 (0.533)	-0.0143 (-0.512)	-0.0172 (-0.690)
$\varepsilon^2_{2,t}$	0.0000 (0.106)	0.1737*** (5.406)	0.0070 (1.199)	0.0059 (0.634)	0.0257 (0.955)	0.0003 (0.092)
$\varepsilon_{2,t}\varepsilon_{2,t}$	0.0013 (0.209)	0.1276** (3.028)	0.0415* (2.251)	0.0222 (1.000)	0.2197* (1.834)	0.0030 (0.158)
$\varepsilon_{2,t}\varepsilon_{3,t}$	0.0006 (0.210)	0.07805* (2.355)	-0.0092 (-1.269)	0.0765 (1.218)	0.0359 (1.061)	0.0027 (0.167)
$\varepsilon_{2,t}\varepsilon_{4,t}$	0.0010 (0.204)	-0.0167 (-1.001)	-0.0027 (-0.736)	-0.0048 (-0.851)	0.1615* (1.85)	-0.0009 (-0.212)
$\varepsilon_{2,t}\varepsilon_{5,t}$	-0.0001 (1.961)	0.0392* (2.033)	-0.0030 (-0.807)	0.0024 (0.539)	-0.0067 (-0.497)	0.0020 (0.182)
$\varepsilon^2_{3,t}$	0.0116* (1.826)	0.0234 (1.628)	0.0613** (3.217)	0.0208 (1.001)	0.4688*** (3.789)	0.0085 (0.339)
$\varepsilon_{3,t}\varepsilon_{3,t}$	0.0112* (1.826)	0.0287* (1.902)	-0.0273 (-1.376)	0.1442* (1.936)	0.1531 (1.334)	0.0151 (0.485)
$\varepsilon_{3,t}\varepsilon_{4,t}$	0.0166** (3.264)	-0.0061 (-0.970)	-0.0078 (-0.749)	-0.0090 (-0.886)	0.6896*** (6.355)	-0.0050 (-0.602)
$\varepsilon_{3,t}\varepsilon_{5,t}$	-0.0029 (-0.951)	0.0144 (1.638)	-0.0090 (-0.899)	0.0045 (0.538)	-0.0287 (-0.520)	0.0113 (0.618)
$\varepsilon^2_{4,t}$	0.0027 (1.040)	0.0088 (1.224)	0.0030 (0.701)	0.2486*** (4.318)	0.0125 (0.680)	0.0066 (0.495)
$\varepsilon_{4,t}\varepsilon_{4,t}$	0.0080* (1.956)	-0.0037 (-0.960)	0.0018 (0.728)	-0.0312 (-0.963)	0.1126 (1.362)	-0.0044 (-0.513)
$\varepsilon_{4,t}\varepsilon_{5,t}$	-0.0014 (-0.893)	0.0088 (1.598)	0.0020 (0.757)	0.0156 (0.571)	-0.0047 (-0.483)	0.0100 (0.845)
$\varepsilon^2_{5,t}$	0.0060* (2.505)	0.0004 (0.501)	0.0003 (0.390)	0.0010 (0.482)	0.2536*** (5.655)	0.0007 (0.237)
$\varepsilon_{5,t}\varepsilon_{6,t}$	-0.0021 (-0.956)	-0.0019 (-0.870)	0.0006 (0.618)	-0.0010 (-0.471)	-0.0211 (-0.515)	-0.0034 (-0.448)
$\varepsilon^2_{6,t}$	0.0002 (0.493)	0.0022 (1.013)	0.0003 (0.449)	0.0003 (0.286)	0.00044 (0.258)	0.0038 (0.879)

Note: ***, **, * are 1%, 5% and 10% respectively. Also $\varepsilon_{21,t}$, $\varepsilon_{22,t}$, $\varepsilon_{23,t}$, $\varepsilon_{24,t}$ $\varepsilon_{25,t}$ and $\varepsilon_{26,t}$ represents the shocks in each model for different food commodities. $\varepsilon_{1,t}\varepsilon_{2,t}$, $\varepsilon_{1,t}\varepsilon_{2,t}$, ..., $\varepsilon_{6,t}\varepsilon_{5,t}$ represents the cross shocks among the food individual food commodities and world crude oil

Results from the analysis further showed $\boldsymbol{\varepsilon^2_{1,1}}$, $\boldsymbol{\varepsilon^2_{2,2}}$, $\boldsymbol{\varepsilon^2_{3,3}}$, $\boldsymbol{\varepsilon^2_{4,4}}$, $\boldsymbol{\varepsilon^2_{5,5}}$ and $\boldsymbol{\varepsilon^2_{6,6}}$, statistically significant indicating prices of meat, dairy, cereal, edible oil, sugars and crude oil price returns depends on its first lags at 1% except for dairy which was 5% significant. Generally, returns of commodity prices are dependent on their lags (Li and Majerowska, 2008; Chang *et al.* 2011). Also, a negative shock was observed between meat and dairy price indices explaining an increase in meat prices during the bird flu period saw a decrease in dairy products other livestock.

Indirect positive shocks were observed cereal and sugar to meat. Bi-directional shocks were observed between each of the series at various significant levels. Secondly, cross-effects were observed between $\varepsilon_{1,t}\varepsilon_{3,t}$, $\varepsilon_{1,t}\varepsilon_{4,t}$, $\varepsilon_{1,t}\varepsilon_{5,t}$, $\varepsilon_{2,t}\varepsilon_{2,t}$, $\varepsilon_{2,t}\varepsilon_{3,t}$, $\varepsilon_{2,t}\varepsilon_{4,t}$, $\varepsilon_{2,t}\varepsilon_{5,t}$, $\varepsilon_{3,t}\varepsilon_{3,t}$, $\varepsilon_{3,t}\varepsilon_{4,t}$, $\varepsilon_{3,t\varepsilon 5},_t$, $\varepsilon_{4,t}\varepsilon_{4,t}$ and $\varepsilon_{5,t}\varepsilon_{6,t}$ and showed a unidirectional spillover from meat to dairy, cereal and sugar. This observation was due to a number of factors such as global economic crisis, the instability in the oil producing countries causing hikes in oil and food prices. Results from the analysis further revealed that previous year's crude oil returns had no effect and hence lag crude oil returns are not transmitted to current general food prices. This is confirmed by price regulations in the global oil market where current crude oil prices are not fixed on past crude oil prices.

Parameter Estimates for Conditional Variances

Table 3 below shows results of the conditional variance estimates of the multivariate GARCH effects and examines estimates of the time-varying variance-covariance. There was a linkage in terms of returns and volatility transmission between returns of meat, dairy, cereal, sugar edible oil and sugar with their lags. This is evident in the positive significance for $h_{11,t}$, $h_{22,t}$ $h_{33,t}$, $h_{44,t}$, $h_{55,t}$ as well as $h_{66,t}$. This confirms an own price volatility transmission from previous months' price returns to current month's price returns. There were volatility spillovers from all the food commodities including crude oil price returns to meat and shows how meat production, processing and consumption is key to global food and nutrition security. This was critical during the 2006-2008 global food crisis period where food prices were on the increase due to scarcity. All was positively influencing meat prices except for a negative crude oil price return. Also there was a negative shock transmitted from meat to dairy since they are all livestock products. Results from the estimated conditional variances (volatilities) estimates for $h_{11,t}$, $h_{22,t}$ $h_{33,t}$, $h_{44,t}$, $h_{55,t}$ and $h_{66,t}$ were all statistically significant, indicating a strong GARCH (1, 1) process influencing the conditional variances of the six indices. Shocks were also observed from dairy to edible oil. Dairy products also experienced price volatility transmission effect with the exception of crude oil price return. This is evident in the efficient supply chains for dairy product. Price volatility transmissions were also observed for cereal, edible oil as well as sugar. That is, a price change in crude oil is transmitted to meat and sugar hence the instability in most agricultural commodity markets due largely to the competition for cereals for both human and energy usage. Also, from cereals to meat, dairy, sugar and crude oil. This confirms the contribution of cereals as a source of feed for livestock and also, cereal being used as a source of energy for biofuel production. Volatility spillover effects were observed from crude oil price returns to meat and sugar price indices.

Table 3: Multivariate GARCH estimates for meat, dairy, cereal, edible oil and crude oil price returns

Independent variable	$h_{11,t+1}$	$h_{22,t+1}$	$h_{33,t+1}$	$h_{44,t+1}$	$h_{55,t+1}$	$h_{66,t+1}$
$h_{11,t}$	0.8095***	0.0503***	0.0020	0.1182***	0.0370*	0.91361***
	(47.901)	(4.072)	(0.938)	(3.575)	(2.176)	(5.186)
$h_{21,t}$	0.0783***	0.4071***	0.0022	-0.0649**	0.1741***	0.2277**
	(3.958)	(7.769)	(1.175)	(-3.210)	(3.991)	(2.9191)
$h_{31,t}$	0.9885***	0.0727***	-0.0132*	-0.4143***	0.5018***	0.7044**
	(39.168)	(4.762)	(-1.747)	(-4.782)	(4.454)	(3.268)
$h_{41,t}$	-0.1150***	-0.0441***	-0.0225*	-0.3381***	-0.0199*	0.0351
	(-6.281)	(-4.905)	(-1.878)	(-9.683)	(-1.996)	(0.256)
$h_{51,t}$	0.0833***	0.0414***	0.0065*	-0.0588***	-0.2059***	0.3637***
	(7.133)	(4.877)	(2.000)	(-3.723)	(-4.383)	(5.339)
$h_{61,t}$	-0.1022***	0.0003	-0.0026*	-0.0872***	0.0384**	1.7824***
	(-9.810)	(0.067)	(-2.039)	(-5.084)	(2.835)	(11.032)
$h_{22,t}$	0.0019*	0.8242***	0.0006	0.0089*	0.2047***	0.0142
	(2.000)	(23.968)	(0.838)	(1.672)	(4.919)	(1.573)
$h_{32,t}$	0.0478**	0.2944***	-0.0074	0.1136***	1.1800***	0.0878*
	(3.864)	(23.968)	(-1.623)	(3.346)	(8.009)	(2.082)
$h_{42,t}$	-0.0056***	-0.1787***	-0.0126*	0.0927**	-0.0467*	0.0044
	(-2.699)	(-5.994)	(-1.663)	(3.116)	(-1.885)	(0.257)
$h_{52,t}$	0.0040***	0.1675***	0.0037*	0.0161**	-0.4842***	0.0453**
	(3.313)	(6.678)	(1.725)	(3.486)	(-8.931)	(2.629)
$h_{62,t}$	-0.0049***	0.0011	-0.0014*	0.0239**	0.0904**	0.2222**
	(-3.903)	(0.067)	(-1.656)	(2.983)	(3.064)	(3.109)
$h_{33,t}$	0.3017***	0.0263***	0.0221***	0.3629***	1.7009***	0.1358
	(20.43)	(3.479)	(7.158)	(5.819)	(12.953)	(1.603)
$h_{43,t}$	-0.0702***	-0.0319***	0.0751***	0.5925*** (19.333)	-0.1347*	0.0135
	(-6.143)	(-3.902)	(11.748)		(-1.907)	(2.640)
$h_{53,t}$	0.0508***	0.0299***	-0.0219***	0.104***	-1.3959***	0.1402**
	(6.875)	(4.470)	(-8.927)	(4.439)	(-15.523)	(2.640)
$h_{63,t}$	-0.0624***	0.0002	0.0086***	0.1528***	0.2605***	0.6873**
	(-11.281)	(0.067)	(4.726)	(5.659)	(3.503)	(3.175)
$h_{44,t}$	0.0041**	0.0097**	0.0637***	0.2418***	0.0027	0.0003
	(3.252)	(2.985)	(12.619)	(7.949)	(0.963)	(0.130)
$h_{54,t}$	-0.0059***	-0.0182***	-0.0371***	0.0841***	0.0553*	0.0070
	(3.252)	(-5.951)	(-9.044)	(4.702)	(1.850)	(0.259)
$h_{64,t}$	0.0073***	-0.0001	0.0146***	0.1247***	-0.0103***	0.0342
	(6.289)	(-0.067)	(4.127)	(5.698)	(-3.492)	(0.261)
$h_{55,t}$	0.0021**	0.0085***	0.0054***	0.0073*	0.2864***	0.0362***
	(3.541)	(3.431)	(5.254)	(2.458)	(10.632)	(3.639)
$h_{65,t}$	-0.0053***	0.0001	-0.0043***	0.0216***	-0.1068***	0.3548***
	(-5.755)	(0.067)	(-3.828)	(3.342)	(-3.492)	(7.073)
$h_{66,t}$	0.0032***	0.0000	0.0008*	0.0161***	0.010*	0.8694***
	(4.967)	(0.034)	(2.113)	(3.342)	(1.775)	(31.415)

Note: ***, **, * are significant at 1%, 5% and 10% respectively. h_{11}, h_{22}, h_{33}, h_{44}, h_{55} and h_{66} denotes the conditional variances for meat, dairy, cereal, edible oil, sugar and crude oil price returns respectively.

Diagnostic Test on the six-variable asymmetric GARCH model

Table 4 below also shows results of a diagnostic test including the likelihood ratios confirming the six return series analysed simultaneously by the BEKK approach. That is, restrictions were placed on the six-variable asymmetric GARCH model such that the cross-commodities of the diagonal parameters and the coefficients in the six-covariance equations were all set to zero. These restrictions ensured that the conditional variances of the six return series were independent. The asymmetric GARCH model with the restrictions was approximated to the six multivariate GARCH models. The first likelihood ratio test for the six-variable asymmetric GARCH model versus the multivariate asymmetric GARCH model was -755.367, we can accept the null hypothesis that the cross-commodities of the diagonal parameters and the coefficients in the six covariance equations are all zero. The six-variable asymmetric GARCH model is however not appropriate and we are right in modelling the six series simultaneously.

The statistic from likelihood test 2 for the six-variable asymmetric GARCH model was -863.8, hence the null hypothesis that the elements in matrix B are zero is rejected. This can be included in asymmetric responses when modelling the six indices. Based on the diagnostic test, we conclude that the six-variable asymmetric GARCH-BEKK model is appropriate for model specification. Finally, the multivariate Ljung-Box (MLBQ) test was performed in order to check for serial correlation of the cross moment (Hosking 1981). The insignificant MLBQ statistic further confirmed previous findings that the BEKK model is appropriate in explaining the conditional heteroscedasticity of the data and successful in capturing the volatility linkages.

Table 4: Diagnostic test on the seven-variable asymmetric GARCH model

Test statistics	**Meat (i=1)**	**Dairy (i=2)**	**Cereal (i=3)**	**Edible Oil (i=4)**	**Sugar (i=5)**	**CrudeOil (i=6)**
LBQ(6)	7.525	13.871	10.328	23.131	2.689	9.15
Prob	0.28	0.031	0.112	0	0.846	0.165
LB Q(12)	31.723	17.455	17.644	28.712	5.99	16.67
Prob	0.002	0.133	0.127	0.004	0.916	0.162
LBQ(40)	99.966	131.154	58.836	71.376	43.789	66.377
Prob	0	0	0.028	0.001	0.313	0.005
MLL(6)	1.836	4.8965	2.663	9.104	2.586	0.156
Prob	0.934	0.557	0.85	0.167	0.858	0.999
MLL(12)	6.860	29.052	10.6	12.704	7.894	6.67
Prob	0.867	0.004	0.564	0.39	0.793	0.878
MLL(40)	32.625	50.2373	39.396	34.946	28.045	10.42
Prob	0.79	0.129	0.497	0.697	0.922	1
LLR	-755.367	-863.8	-860.572	-931.279	-1047.03	-969.891

Conditional Cross-Correlations

Results from the analysis further showed interesting relationships among the various commodities. Based on the objective of the paper, there were strong correlations between the individual food prices indices and crude oil price returns. This is confirmed by Busse et al. (2011) who asserted that increasing positive correlation between energy prices and agricultural commodities. These are shown in the figure 1 below. This can be attributed to the emergence of biofuel which uses sugars and cereal as raw materials as alternative energy source. Previous study by Abdelradi and Serra (2015) found some past turbulence in sugar and crude oil markets in the Spanish energy industry due to its quick response to changes in world crude oil prices.

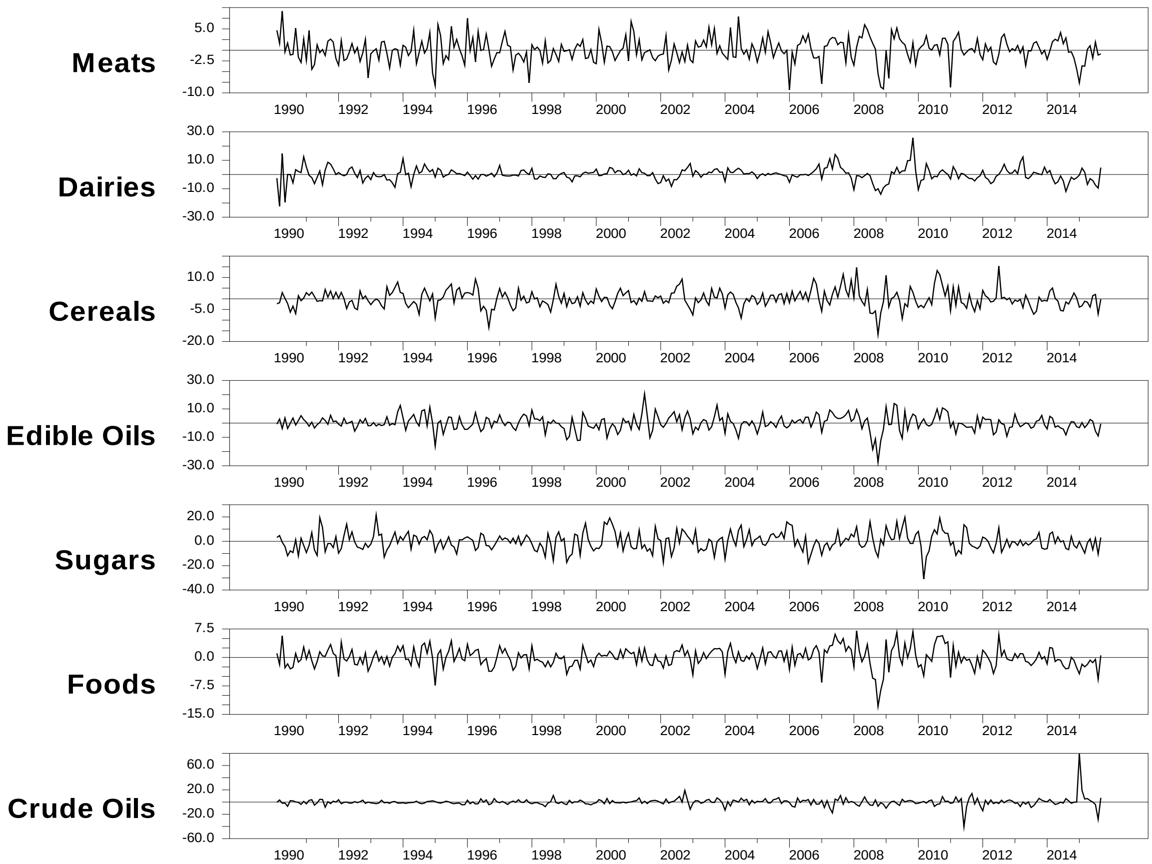

Figure 1. Conditional cross-correlations between crude oil price returns and individual food price indices

CONCLUSION

Agricultural commodity prices are still influenced by changes in world crude oil prices. This is shown in volatility spillover effects from world crude oil price returns to meat and sugar consumer price index returns. These two commodities constitute a large part of agricultural food commodities due to human and industrial demands. The high volatility transmitted to sugar has witnessed increasing and unstable sugar prices largely due to biofuel and the demand for this commodity by the confectionary industries. Also, volatility transmitted to meat is observed in the cost transferred to meat processing and handling. This can also be attributed to the influx of bird flu (Avian Influenza) virus and hence a restriction on chicken consumption causing a high substitution effect where consumers prefer beef to chicken hence an increase in price of beef. The volatility spillover between real crude oil returns and the meat, cereal, edible oil, and sugar price indices was low except in 2015 where there was a high volatility effect. This is also attributed to hikes in world crude oil prices and hence a corresponding increase in general food prices. The correlations increased as far as from -0.4 to 0.4. cross-effects were observed between $\varepsilon_{1,t}\varepsilon_{3,t}$, $\varepsilon_{1,t}\varepsilon_{4,t}$, $\varepsilon_{1,t}\varepsilon_{5,t}$, $\varepsilon_{2,t}\varepsilon_{2,t}$, $\varepsilon_{2,t}\varepsilon_{3,t}$, $\varepsilon_{2,t}\varepsilon_{4,t}$, $\varepsilon_{2,t}\varepsilon_{5,t}$, $\varepsilon_{3,t}\varepsilon_{3,t}$, $\varepsilon_{3,t}\varepsilon_{4,t}$, $\varepsilon_{3,t}\varepsilon_{5,t}$, $\varepsilon_{4,t}\varepsilon_{4,t}$ and $\varepsilon_{5,t}\varepsilon_{6,t}$ and showed a unidirectional shocks from cereal and sugar to meat price index.

Cereal and sugars also transferred shocks to dairy price indices due to livestock feed production. This observation was due to the indirect effect of crude oil price returns transmitted to general food price indices. Also the global crude oil price shocks and volatility transmissions are as a result of the instability in Middle

East which also forms largest source of world crude oil. This is also attributable to discovery of biofuel as an alternative energy source which uses cereals as a raw material. This further confirms the role energy plays in world food commodity prices and its effect on national policy formulation and development. Determination of crude oil price transmission to food markets will also provide information to investors and entrepreneurs of food processing industry in the agricultural commodity markets for planning and efficiency in production.

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