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FOOD SCIENCE & TECHNOLOGY | RESEARCH ARTICLE

Oil price and food price volatility dynamics: The case of Nigeria

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Abstract: This study examines the long and short run relationships between oil price and food price volatility as well as the causal link between them. The study used annual food price volatility index from FAO from 2000 to 2013 and crude oil price from U.S. Energy Information and Administration (EIA) from 2000 to 2013. The Johansen and Jesulius co-integration test revealed that there is a long run relationship between oil price and domestic food price volatility. The vector error correction model indicated a positive and significant short run relationship between oil price and food price volatility. The Granger causality test revealed a unidirectional causality with causality running from oil price to food price volatility but not vice versa. It is recommended that policies and interventions that will help reduce uncertainty about food prices such as improved market information, trade policies and investment in research and development among others should be encouraged. Also to reduce the effect of oil price shock, it is recommended that government should subsidise pump price of refined oil, seek alternative sources of energy and there should be less dependence on oil for fertilizer production.

ABOUT THE AUTHORS

Ijeoma C Nwoko obtained her MSc in Agricultural Economics from Federal University of Agriculture Makurdi, Nigeria, in 2015. She has the intention of advancing her research capabilities in by enrolling for her doctorate degree and creating both local and international networks. She has interest in energy and environmental economics.

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PUBLIC INTEREST STATEMENT

Crude oil price affects food price volatility directly and indirectly. Crude oil is used in the manufacturing of fertilizer, powering of production and processing machines and transporting agricultural commodities and other finished goods to end users. A shock in crude oil price creates uncertainty which affects investment in agricultural production. This may affect the level of agricultural output and the supply of food and hence the price. The hike in oil price has also led to the discovery and use of biofuel as an alternative source of energy. In the production of biofuel, some agricultural commodities such as corn and soyabean are used as feed stock. This leads to competition for available land and water and hence supply and price of food. We empirically examine this link and find that oil price has significant increasing effect on Nigeria's aggregate food price both in the long and short terms.

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1. Introduction

There has been a global concern over oil price and food price volatility since the global food crisis of 2007–2008 and the resurgence of food price crisis in 2010. Sequel to this development, in June 2011, the ministers of Agriculture of the G20 countries prepared an action plan to address food price volatility (G20 (Group of 20), 2011). The 2011 *Global Hunger Index*, prepared by the International Food Policy Research Institute (IFPRI), adopts food price volatility as the special theme for 2011 (IFPRI, 2011). Food volatility refers to variations in food prices over time.

In most developing countries, instability in the price of staple foods is an important source of risk and poses a threat to the food security situation of the country. The urgency to address the food price volatility is a step forward towards addressing the insecurity situation of the country. Volatile food prices stimulated by changes in energy prices may increase the risk exposure of smallholders, altering hedging and investment decisions and promoting speculative activity in agricultural production (Gardebrock & Hernandez, 2012). It is also feared to have a ravaging impact on the poor as greater percentage of their family budget is spent on food.

Periods of high or low prices are not new. In fact, price variability is at the core of the very existence of markets. However, since 2007, the degree of price volatility and the number of countries affected have been very high. This is why food volatility in the context of higher food price has generated considerable anxiety and caused real problems in many countries (High Level Panel of Experts, 2011). Food price volatility over the last four years has hurt millions of people, undermining nutritional status and food security (High Level Panel of Experts, 2011). Volatility in the international market has recently increased (Minot, 2011). Given that Nigeria is a net food importer, it is natural to assume that volatility in the international market would be transmitted to domestic market in Nigeria.

Energy prices, among other factors, have been considered as one of the causes of food price instability. High oil prices may affect food prices directly and indirectly. This is because modern agriculture uses oil products to fuel farm machinery, processing equipment, transport other inputs to the farm and to transport farm output to the ultimate consumers. Moreover, fertilizer production is dependent on oil. Increase in oil prices therefore puts pressure on all these aspects of commercial food system. Thus, there is concern that high and volatile prices of crude oil may cause food prices to continue to increase (Bloomberg, 2011 cited in Heinberg, 2011).

As far as oil price and food and/or agricultural price volatility are concerned, there are also a number of studies. This is particularly so since the recent food crises in 2007–2008 and 2009–2010 have drawn the attention of researchers on the increased volatility of agricultural commodities. For instance, Huchet-Bourdon (2011) statistically analyse the historical commodity price volatility over the last half century for an extended range of agricultural commodities such as beef, maize butter, rice, soybean oil, sugar, wheat and whole milk. The paper also investigated the relationship between oil price, fertilizer price and each of these agricultural commodities using Spearman's correlation coefficient on monthly data. The paper also concluded that a causal effect exists between the changes in crude oil price, fertilizer price, etc. and the changes in each of the agricultural commodity price series. It is also concluded that there is no increasing tendency in price volatility over the past 50 years for individual agricultural product price. However, in general, price volatility in the recent period of 2006–2010 was higher than that in the 1990s but not higher than that of the 1970s.

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In the same vein, Sujithan, Avouyi-Dovi, and Kolia (2014) used Bayesian multivariate framework to assess the effect of oil price and other drivers on the volatility of global prices of cocoa, coffee, sugar and wheat in recent periods. Using monthly data covering the period from January 2001 to March 2013, an impulse response function of food volatility to oil price shocks revealed that an oil price shock leads to an increase in the price volatility of cocoa, coffee, sugar and wheat for 2–3 months, followed by a downward peak after 4 months. The result showed a negative impact on the volatility of soybeans and sugar and a positive impact on cocoa, coffee, corn and wheat prices.

Gilbert and Morgan (2010) conducted an analysis to ascertain the assumption that international food price volatility has risen over time. Using generalised autoregressive conditional heteroscedasticity (GARCH) model, they analysed monthly food prices between 1970 and 2009 and 1990 and 2009 for the purpose of comparison. The result revealed that volatility has increased over the most recent years, but there have also been periods of high volatility in the past and the recent episode does not appear exceptional. It is therefore possible to hope that volatility levels will drop back to historical levels. This is also in line with the findings of Huchet-Bourdon (2011), even though they mentioned some other factors which they feared could lead to future increase in volatility such as global warming and oil price volatility. This implies that with increase in these factors, there are possibilities of increased volatility in the future.

Furthermore, Fondazione (2013) analysed volatility in food commodities and its co-movement with crude oil prices. DCC-MGARCH models were used to estimate daily logarithmic prices over the 12-year sample 2000–2011 using international prices. His findings revealed the empirical evidence that increased volatility in grains during the 2008–2009 spike was substantially due to shocks transmitted from crude oil to grains, especially corn, wheat and soybean prices, but contributed relatively less at other times.

Minot (2011) studied price volatility in Africa with the aim of verifying the assumption that African food price has become more volatile recently. Using F-statistics, he tested the changes in price volatility between 1980 and 2006 and 2007 and 2010. His analysis for both 2011 and 2013 studies, respectively, revealed that food price volatility in the international market has increased in the past five years, though it is still relatively low. However, the result showed that in a group of 11 African countries, food price volatility is high and has not increased in recent years.

The studies reviewed used international food prices. We contribute to the literature by considering the domestic food price volatility. Specifically, this study seeks to describe the properties and trend of world oil price and Nigeria's food price volatility; examine the long run and short run impact of oil price on domestic food price volatility. We also analyse the causal relationship between oil price and food price volatility.

2. Methodology

2.1. Data
The study used time series data which are secondary data type. The study used the aggregate domestic food price volatility index from FAO which spans from 2000 to 2013. Annual data on oil price (Refiner Acquisition Cost of Imported Crude Oil) were obtained from the U.S. Energy Information Administration (EIA).

2.2. Econometric methodology
Data for this study were analysed using descriptive and inferential statistics. To describe the properties and trend of the time series, descriptive statistics such as mean, standard deviation, kurtosis, skewness and Jarque–Bera test of normality of the series were used. Also graphs were used to describe the trend or movement of price volatility of these crops and oil prices from 2000 to 2013. To check for the stationarity or non-stationarity of the series, the Augmented Dickey–Fuller and Phillip–Perron tests were used. The Johansen (Johansen, 1995; Johansen & Juselius, 1991) co-integration

test was used to examine the long run relationship, while vector error correction model (VECM) was employed to determine the short run relationship between oil prices and food price volatility. The use of VECM is based on the outcome of the co-integration test. The Granger causality (1969) approach was used for examining the causal relationship.

2.2.1. Unit root test

To establish whether or not each series is stationary, unit root tests were carried out. The need to test for the presence of unit root is to avoid the problem of spurious regression as described by Granger and Newbold (1974) cited by Gogoi (2014). If unit root is found, then the conditions of stationarity are violated. The most commonly used test is the augmented Dickey–Fuller test (ADF). The test equation for food price volatility is given as:

$$\Delta \, \text{FPVOL}_t \, = \, \alpha_0 \, + \, \alpha_1 t \, + \, \beta \text{FPVOL}_{t-1} + \sum_{i=1}^{p} \delta_i \, \Delta \, \text{FPVOL}_{t-i} \, + \, \varepsilon_t \qquad (1)$$

where FPVOL is the food price volatility, α_0 is the constant, α_1 is the coefficient of the trend series, p is the lag order of the autoregressive process, FPVOL_{t-1} is the lagged value of order one of FPVOL_{t-1} and ε_t is the error term. Dickey–Fuller adds lagged dependent variables to the test equation to remove distortions to the level of statistical significance but lowers the power of the test to detect a unit root when one is present. The null hypothesis can be evaluated by testing whether $\beta = 0$, while the alternative hypothesis tests whether $\beta < 0$. A rejection of the null hypothesis implies that the series is stationary. The oil price unit root test was also performed in a similar manner and the model is given as:

$$\Delta \, \text{OILP}_t \, = \, \alpha_0 \, + \, \alpha_1 t \, + \, \beta \text{OILP}_{t-1} + \sum_{i=1}^{p} \delta_i \, \Delta \, \text{OILP}_{t-i} \, + \, \varepsilon_t \qquad (2)$$

where OILP stands for oil price and all other parameters are as previously defined. For robustness check, the PP unit root test was also conducted.

2.2.2. Co-integration test

If variables OILP and FPVOL have unit roots, but some linear combination of them is stationary, then the spurious regression which occurs when variables are non-stationary can be taken care of or avoided because OILP and FPVOL are co-integrated (Koop, 2000). According to Engle and Granger (1987), two series integrated of the same order I(q) are said to be co-integrated, if the linear combination of the two variables generates a stationary series. A non-stationary series that is co-integrated may diverge in the short run but must be linked together in the long run. The co-integrated variables will never move far apart, and will be attracted to their long run relationship (Koop, 2000). Testing for co-integration implies testing for the existence of such a long run relationship between economic variables.

Although there are different ways of testing for co-integrations between variables, for the purpose of this study, the Johansen co-integration test was used to determine the long run relationship between food commodity price volatility and oil prices. It is superior to other tests and has all desirable statistical properties. It is capable of determining the number of co-integrating relations among variables. Its weakness is that it relies on asymptotic properties and is therefore sensitive to specification. According to this technique, to determine whether two variables are co-integrated, we first have to ascertain the order of integration of the variables that are being modelled. This pre-testing is done by the unit root test as earlier discussed. To proceed with the co-integration test in the Johansen framework, the two variables have to be integrated of the same order. If we establish that two variables are integrated of the same order, then we proceed next to estimating the long run equilibrium relationship. The Johansen test is a VAR-based co-integration test. Consider a general VAR of order p:

$$y_t \;=\; A_1 y_{t-1} + \ldots + A_p y_{t-p} + B\, x t_{t-i} \;+\; \varepsilon_t \tag{3}$$

where y_t is a *k*-vector of non-stationary variables that are, for instance, integrated of order 1 and commonly denoted as I(1). In this study, y_t consists of OILP$_t$ and FPVOL$_t$, x_t is a d-vector of deterministic or exogenous variables which are optional and ε_t is a vector of innovations or random shocks. The VAR may be rewritten as

$$\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + B x_t + \varepsilon_t \tag{4}$$

where

$$\Pi = \sum_{i=1}^{p} A_i - I, \quad \Gamma_i = - \sum_{j=i+1}^{p} A_j \tag{5}$$

Granger's representation asserts that if the coefficient matrix *Π* has reduced rank *r* < *k*, then there exist matrices α and β each with a rank *r* such that $\Pi = \alpha\beta'$ and $\beta' y_t$ is I(0). *r* is the number of co-integrating relationships (i.e. the co-integrating rank) and each column of β is the co-integrating vector. The elements of α are known as the adjustment parameters in the VEC model. Johansen's method is to estimate the Π matrix from an unrestricted VAR and to test whether we can reject the restrictions implied by the reduced rank of Π. It can be shown that for a given r, the maximum likelihood estimator of β defines the combination of y_{t-1} that yields the *r* largest canonical correlations of Δy_t with y_{t-1} after correcting for lagged differences and deterministic variables when present. For this study, deterministic or exogenous variables such as seasonal dummies and time trends are not included. Johansen proposes two different likelihood ratio tests of the significance of these canonical correlations and thereby the reduced rank of the Π matrix: the trace test and maximum eigenvalue test. The trace test tests the null hypothesis of *r* co-integrating vectors against the alternative hypothesis of *k* co-integrating vectors. The maximum eigenvalue test, on the other hand, tests the null hypothesis of *r* co-integrating vectors against the alternative hypothesis of *r* + 1 co-integrating vectors.

2.2.3. Vector error correction model
The co-integrating relationship only takes care of the long run relationship but does not take care of the short run dynamics explicitly. A good time series model must describe both the long run and short run effects of individual variables. It is defined as a dynamic model in which the movement of the variable in any period is related to the previous period's gap from the long run equilibrium. It is the speed at which a dependent variable, *Y*, returns to equilibrium after a change in an independent variable, *X*.

Granger's "Representation Theorem" states that for every co-integrated relationship, there must exist a mechanism by which the equilibrium is maintained. Even when there exists a long run relationship, there will be deviations from the equilibrium and the correction or the adjustment process is described by what is known as VECM. The VECM, often also denoted as VECM, is a restricted VAR designed for use with non-stationary series that are known to be co-integrated.

A simple formulation of two variable systems with one co-integrating equation and no lagged difference terms is represented as follows:

$$\text{OILP}_t = \beta_1 \text{FPVOL}_t \tag{6}$$

The corresponding VEC model is:

$$\Delta \text{OILP}_t = \alpha_1 \big(\text{FPVOL}_{t-1} - \beta_1 \text{OILP}_{t-1} \big) + \varepsilon_{1,t}$$

$$\Delta\text{FPVOL}_t = \alpha_2\big(\text{FPVOL}_{t-1} - \beta_1\text{OILP}_{t-1}\big) + \varepsilon_{2,t} \tag{7}$$

In this simple model, the only right-hand side variable is the error correction term. In long run equilibrium, this term is zero. However, if OILP and FPVOL deviate from the long run equilibrium, the error correction term will be non-zero and each variable adjusts to partially restore the equilibrium relation. The coefficient α_i measures the speed of adjustment of the ith endogenous variable towards the equilibrium. If α_i has a negative sign, this ensures that any disequilibrium will be corrected. If α_i tends to −1, then a large percentage of the disequilibria is corrected from each period; if tending to 0, then the adjustment will be slow and if the sign is positive, then it will imply that the system diverges from the long run equilibrium path.

However, if the lagged difference terms and constants are included as done in this study, Equation (7) becomes:

$$\Delta\text{OILP}_t = \delta_0 + \sum_{i=1}^{p}\varphi_i\Delta\text{OILP}_{t-i} + \sum_{i=1}^{p}\gamma_i\Delta\text{FPVOL}_{t-i} + \alpha_1\big(\text{FPVOL}_{t-1} - \beta_0 - \beta_1\text{OILP}_{t-1}\big) + \varepsilon_{1,t}$$

$$\Delta\text{FPVOL}_t = \eta_0 + \sum_{i=1}^{p}\lambda_i\Delta\text{OILP}_{t-i} + \sum_{i=1}^{p}\theta_i\Delta\text{FPVOL}_{t-i} + \alpha_2\big(\text{FPVOL}_{t-1} - \beta_0 - \beta_1\text{OILP}_{t-1}\big) + \varepsilon_{2,t} \tag{8}$$

where δ_0 and η_0 are the constant terms (intercepts) in the oil price and food price volatility equations, respectively. φ_i and γ_i are the coefficients of the lagged oil price and lagged food price volatility, respectively, in the oil price equation, while λ_i and θ_i are the corresponding parameters in the food price volatility equation. β_1 is the co-integrating vector and α_1 and α_2 are the speed of adjustment parameters in the oil price and food price volatility equations, respectively.

2.2.4. Causality test

Correlation does not necessarily imply causation in any meaningful sense of the word. Granger causality measures the precedence or information content or the predictability ability of the past values of one variable for the current values of another variable. According to Granger (1969) causality, if a series Y_1 "Granger-causes" a series Y_2, then past values of Y_1 should contain information that helps predict Y_2 above and beyond the information contained in past values of Y_2 alone. Its mathematical formulation is based on linear regression modelling of stochastic processes.

The basic Granger causality definition is quite simple. If we have two time series OILP_t and FPVOL_t and we attempt to forecast FPVOL_t using past terms of OILP_t, then OILP_t is said to "Granger cause" FPVOL_t if OILP_t helps in the prediction of FPVOL_t. The definition leans on the idea that cause occurs before the effect and this is basis of most, if not all, causality definitions. It also must be noted that we determine if there is a two-way causality, that is, if OILP_t causes FPVOL_t and FPVOL_t causes OILP_t.

The causality relationship can be evaluated by estimating the following linear regression models. Consider a bivariate linear autoregressive model of the two variables OILP_t and FPVOL_t. The important thing to point out here is that if the variables have a trend, then it is most likely to show that there is a correlation between them. However, in general, correlation doesn't mean causation as earlier stated. So Granger causality test is important as it highlights the presence of causation and it can be unidirectional or two-way causation. The empirical bivariate regression model is specified as:

$$\text{OILP}_t = \delta_1 + \sum_{i=1}^{p}\varphi_{11,i}\text{OILP}_{t-i} + \sum_{i=1}^{p}\varphi_{12,i}\text{FPVOL}_{t-i} + \varepsilon_{1,t}$$

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$$\text{FPVOL}_t = \delta_2 + \sum_{i=1}^{p} \varphi_{21,i}\text{OILP}_{t-i} + \sum_{i=1}^{p} \varphi_{22,i}\text{FPVOL}_{t-i} + \varepsilon_{2,t} \qquad (10)$$

where p is the number of lagged observations included in this model which were determined using the Akaike information criteria (AIC) (Akaike, 1974) and the Schwartz information criteria (SIC) (Schwarz, 1978); the matrix φ contains the coefficients of the model; while ε_1, and ε_2, are residuals (prediction errors) for each time series.

According to Gogoi (2014), if the variance of ε_1, or ε_2, is reduced by the inclusion of the FPVOL or OILP terms in the first or second equation, then it is said that FPVOL or OILP Granger causes OILP or FPVOL. In other words, OILP Granger causes FPVOL if the coefficients in $\varphi_{21,i}$ are jointly significantly different from zero. This can be tested by performing an F-test of the null hypothesis that$\varphi_{21,i} = 0$, given assumptions of covariance stationarity on OILP and FPVOL. Analogously, FPVOL Granger causes OILP if the coefficients in $\varphi_{12,i}$ are jointly significantly different from zero. This can be tested by performing an F-test of the null hypothesis that $\varphi_{12,i} = 0$. The hypothesis is as follows:

H_0: OILP$_t$ (or FPVOL) does not cause FPVOL (or OILP$_t$)

H_1: OILP$_t$ (or FPVOL) cause FPVOL (or OILP$_t$)

Rejection of the null hypothesis implies that there is causation from one variable to the other. If the null cannot be rejected, then it means that there is no causal relationship between the variables. In other words, the two variables have no predictive or information content for each other.

3. Results and discussion

3.1. The trend and properties of oil price and food price volatility

The trend of world oil price and Nigeria's food price volatility is presented in Figure 1. The trend shows an undulating movement of the food price volatility (FPVOL) from the 2000 to 2002. Food price volatility was as high as 18 in 2001 and peaked at about 19 in 2004 and went as low as 6 in 2010. It then increased from 2011 to 2012 before it started falling. Figure 1 also indicated that food price volatility from 2007 to 2008 was high in Nigeria which coincided with the time of the global food crises that attracted the attention of the international community to food price volatility. However, it did not show any resurgence in 2010. This implies that international food price volatility may not be a true representation of what the situation is in the domestic market for this period.

The trend in oil price (OILP) shows a gradual and constant increase in oil price from about US$ 27 per barrel in the year 2000 to a high of about US$ 92 per barrel in the year 2008. This movement dropped in the year 2009 and started increasing in the year 2010 and peaked at US$ 102 per barrel in 2011. As of 2013, it stood at about US$ 98 per barrel.

The mean, maximum, minimum, standard deviation, skewness, kurtosis and Jarque–Bera test of normality of the variables are presented in Table 1. Skewness is an indicator or sign of asymmetry and deviation from a normal distribution. The skewness value of zero is an indication that the distribution is symmetrical around the mean. Values greater (less) than zero imply right (left) skewed distribution, respectively, and shows an asymmetric distribution. However, since these values are not exactly zero, one may conclude that food price volatility is skewed to the left, i.e. negatively skewed, while oil price is positively skewed. The null hypothesis of normality cannot be rejected for any of the series as evidenced by the Jarque–Bera test.

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Figure 1. Trend of world oil price and Nigeria food price volatility.
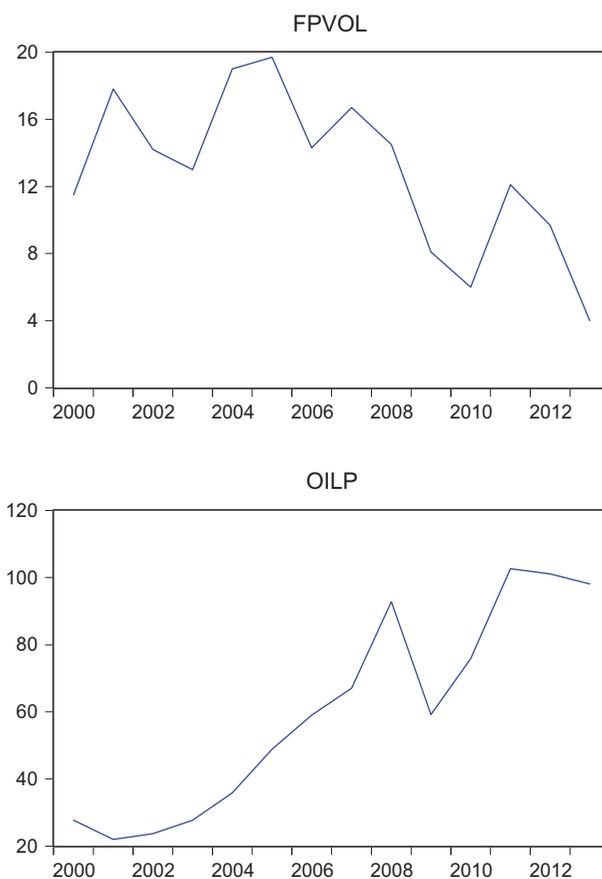
Table 1. Descriptive statistics

	FPVOL	OILP
Mean	12.90	60.11
Maximum	19.70	102.63
Minimum	4.00	22.00
Std. Dev.	4.73	30.24
Skewness	−0.35	0.15
Kurtosis	2.24	1.57
Jarque–Bera	0.62	1.25
Probability	0.73	0.54

Table 2. Augmented Dickey–Fuller and Philip–Perron tests

Variables	Level		First difference		Decision
	T-statistic	Probability	T-statistic	Probability	
ADF					
OILP	−0.765	0.795	−4.177***	0.010	I(1)
FPVOL	0.155	0.954	−5.332***	0.008	I(1)
PP					
OILP	−0.178	0.920	−8.500***	0.000	I(1)
FPVOL	−1.471	0.516	−5.584***	0.001	I(1)

*** Means 1% significance.

Table 3. Johansen co-integration test							
Trace test				**Maximum eigenvalue test**			
H$_o$	**H$_1$**	**Statistic**	**5% CV**	**H$_o$**	**H$_1$**	**Statistic**	**5% CV**
Co-integration test between OILP and FPVOL							
$r = 0$	$r \geq 1$	14.374	15.495	$r = 0$	$r = 1$	14.356**	14.265
$r \leq 1$	$r \geq 2$	0.018	3.841	$r = 1$	$r = 2$	0.018	3.841

Note: CV means critical value.

**Rejection of the null hypothesis at 5% level.

Table 4. Long run estimates of effects of OILP on FPVOL	
OILP	6.5705
	(1.4812)
	[4.4359]***
Constant	−150.045

Notes: Values in bracket are the standard errors, while those in parenthesis are the *t*-statistics.

***Significance at 1% level.

The augmented Dickey–Fuller (ADF) and Philip Perron (PP) unit root tests were used to check for stationarity or non-stationarity of variables. Based on the result presented in Table 2, OILP and FPVOL in levels have unit roots and hence non-stationary, given that the null hypothesis cannot be rejected at any conventional level of significance. However, when the first differences are examined, the null hypothesis of unit root is rejected by both ADF and PP unit root tests at 1% level for both series. Therefore, the two variables are integrated of order one, 1(1).

3.2. Long run analysis

From the first panel of Table 3, the maximum eigenvalue test indicates one co-integrating equation rejecting the null hypothesis that oil price and food price volatility are not co-integrated at 5% level of significance. However, the trace test indicates that there is no co-integration between oil price and food price volatility at 5% level of significance. This implies that we accept the alternative hypothesis that OILP and FPVOL are not co-integrated.

When there is a conflicting co-integration result, the maximum eigenvalue test should be adopted when estimating the error correction model as it has a sharper alternative hypothesis that pins down the number of co-integrating vectors (Enders, 2004). Therefore, we can say that oil price and FPVOL are co-integrated which indicates a long run relationship between the two variables. The long run estimates as shown in Table 4 indicate that OILP has a positive long run effect on FPVOL which is statistically significant at 1%. This implies that 1% increase in OILP will increase FPVOL by 65%. This also implies that the higher the OILP, the higher the FPVOL. It implies that the variables move together over time. Should there be a deviation from their mean level or equilibrium level, it will be easy to bring them back to equilibrium. Although they are individually non-stationary, their linear combination is stationary. Overall, we conclude that oil price and food price volatility have a significant relationship in the long term.

3.3. Short run analysis

Given that there exists a long run relationship between oil price and aggregate food price volatility, the short run analysis will proceed in a VECM framework. The short run analysis is to correct the deviations in the long run from the equilibrium. This analysis determines the speed at which the food price volatility returns to equilibrium after a change or shock in the oil price. First, we can see from Table 5 that the speed of adjustment coefficients, α, (−0.247 for OILP and −0.149 for FPVOL) have

Table 5. VECM estimates of short run analysis between OILP and FPVOL

Error correction	ΔOILP			ΔOILP		
	Coefficient	S.E	t-Statistic	Coefficient	S.E	t-Statistic
α	−0.247	0.211	−1.167	−0.149	0.037	−3.968***
OILP(−1)	−0.154	0.378	−0.408	0.164	0.067	2.446**
FPVOL(−1)	0.938	1.204	0.779	0.067	0.213	0.313
Constant	7.426	5.160	1.439	−2.142	0.915	−2.341**
R^2	0.258			0.674		
F-statistic	0.928			5.508***		

**Significance at 5% level.

***Significance at 1% level.

Figure 2. Impulse response functions between oil price and food price volatility.

Response to Cholesky One S.D. Innovations
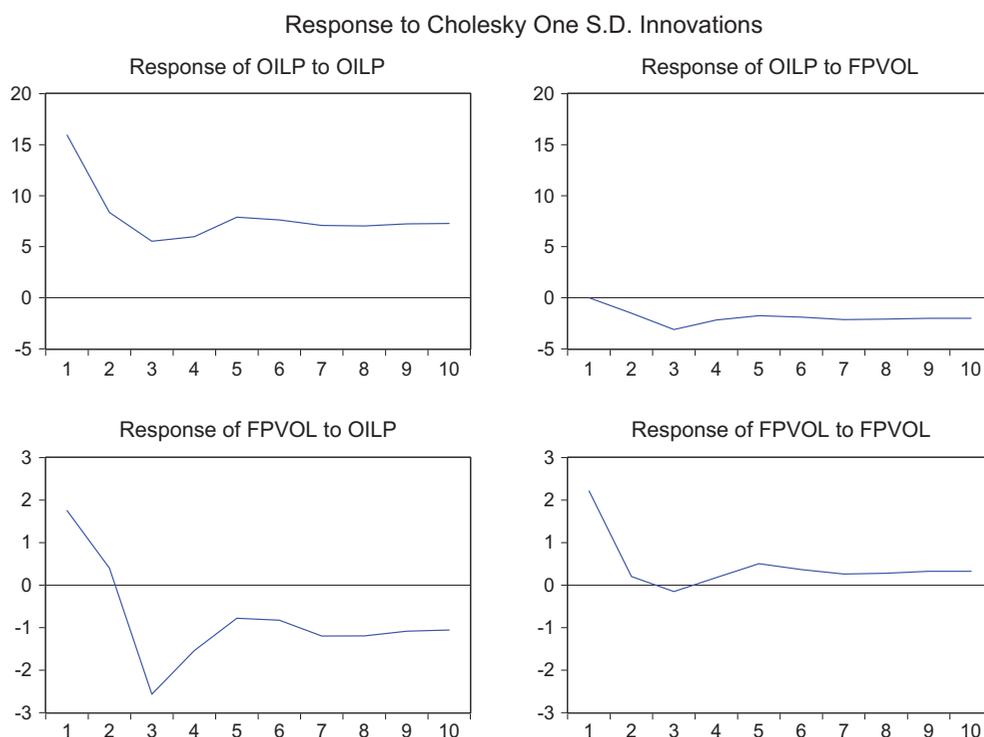
negative sign as expected. This implies that about 15% of the FPVOL deviations from the long run equilibrium were corrected each period.

Short run dynamics interrelationship between the two prices can be better observed by computing the impulse response function which shows the persistent effect of shocks between the two prices. Impulse response function shows the response of variables to one standard deviation shock in itself and in the other variables in the system over time. This study used the Cholesky one standard deviation innovation over 10 years.

Figure 2 shows that the immediate response of aggregate food price volatility to a shock in oil price is positive up to the second year; thereafter, it turned negative and persistent to the end. However, the response of oil price to aggregate food price volatility was negative and persistent to the end.

The variance decomposition of oil price and food price volatility results is displayed in Table 6. Oil price (OILP) contributed 100% of the variations in oil price in the first period, while food price

Table 6. Variance decomposition of OILP and FPVOL			
Equation	**Period**	**OILP**	**FPVOL**
OILP	1	100	0
	5	95.78	4.219
	10	94.634	5.366
FPVOL	1	38.477	61.523
	5	70.877	29.123
	10	76.448	23.552

Table 7. Ganger causality analyses		
Null hypothesis	**Chi square**	**Probability**
OILP does not Granger cause FPVOL	5.984[***]	0.014
FPVOL does not Granger cause OILP	0.606	0.436

[***]Significance at 5%.

volatility (FPVOL) contributed 0%. In the 5th and 10th periods, FPVOL contributed 4.2 and 5.4%, respectively, to the variation in oil price. With respect to the variance decompositions of food price volatility, about 61.5% of the variation in FPVOL was contributed by own shock, while OILP contributed about 38.5% to the variations in food price volatility in the first period. In the 5th and 10th periods, it contributed about 70.9 and 76.4%, respectively, to the variation in aggregate food price volatility. It is thus noted that the contribution of oil price to aggregate food price volatility kept increasing down the period.

3.4. Granger causality test

The causality test is used to forecast or to show if oil price has a predictive power for food price volatility and vice versa. The Granger causality test results are presented in Table 7. From the analysis, it can be seen that oil price Granger causes FPVOL because the Chi-square statistics is significant at 1% as evidenced by the *p*-value. Therefore, we reject the null hypothesis which states that oil price does not Granger cause aggregate food price volatility. However, we cannot reject the hypothesis that FPVOL does not Granger cause oil price. We therefore conclude that there is a unidirectional causality running from oil price to aggregate food price volatility.

4. Conclusion and policy implications

The purpose of this study was to determine the relationship between oil price and food price volatility. Specifically, the study examined the long run and short run relationships between oil price and food price volatility using domestic food prices and also investigated the causality between them. Analysis shows some level of volatility in domestic food prices. Based on Johansen's co-integration test, the study concludes that there exists a long run relationship between oil price and aggregate food price volatility. The VECM for analysing the short run relationship indicates a positive and significant impact of oil price on food price volatility. The study also concludes that there is a unidirectional causality running from oil price to aggregate food price volatility and not vice versa.

These findings have important policy implications. Interventions to reduce food price volatility to its natural level where it will not be a problem to the farmers or threaten the food security in the country are needed. These may be in the form of improvement in the market information system as this would reduce market speculations, price hikes and uncertainty. Trade policies and buffer stock could also be helpful in this regard. Further, adequate public and private investments in agriculture will create a more productive and efficient agricultural sector that will make food more affordable for the poor and reduce price variability.

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Governments should also ensure that pump price of oil or crude oil products is being subsidised to cushion the effect of high oil prices on food prices, even though there are other factors like exchange rates that affect the prices of food, especially for imported food crops. Also governments should encourage alternative source of energy like ethanol and biofuel which have the tendency of bringing down the cost of crude oil products used in production and processing of agro products, despite the fact that these could be linked to increased food volatility as some food crops are being used as feed stock in biofuel production. Governments should encourage the use of commercial production of organic fertilizers which will reduce dependence on oil fertilizers. Governments should ensure that our refineries are operating at their maximum capacity.

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