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FOOD PRICE SENSITIVITY TO CHANGES IN PETROLEUM PRICE AND EXCHANGE RATE IN GHANA: A COINTEGRATION ANALYSIS

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ABSTRACT

This paper investigated how sensitive food price is to changes in petroleum price and exchange rate in Ghana from January 1997 to August 2017. Interest rate was included as a control variable in the study since it may be a useful macroeconomic policy tool. Using Johansen cointegration procedure, Vector Error Correction Model, Impulse Response Functions and BEKK-GARCH estimations, the results of the study showed there exist positive long-run and short-run relationships between food prices and all the macroeconomic variables used in the model. Thus, increases in petroleum price, exchange rate and interest rate raise food prices in Ghana. The magnitudes of these increases were found to be very high during the food crises periods in 2007/08 and 2010/11. It was also found that effects of these food price spikes caused by shocks from petroleum price, exchange rate and interest rate are long lasting and do not decay easily with time. The results from the BEKK-GARCH estimation showed that food prices in Ghana exhibit time-varying volatility; caused by its own ARCH and GARCH effects as well as exogenously determined shocks from petroleum price, exchange rate and interest rate. Also, the results indicated that food price volatility shocks in Ghana are persistent. It is recommended that; policy aimed at food price stabilization must build national petroleum buffer stocks to stabilize fuel prices, improve exchange rate and interest rate management, build district, regional and national food buffer stocks, selectively target fuel subsidy at crop farmers and food processors, and remove bottlenecks in food marketing.

Keywords: **Food Prices; Petroleum Price; Exchange rate; Cointegration; Price volatility; BEKK–GARCH**

1. INTRODUCTION

Petroleum impacts food production in some very important ways. The use of petroleum-derived inputs has increased in agriculture over time. The prices of these critical inputs, then, would be expected to alter supply, and, therefore, the prices of food commodities that use these inputs. At the same time, exchange rates have long been thought to have an important impact on the export and import of goods and services, and, thus, exchange rates are expected to influence the price of those products that are traded. Crude oil and about 65% of rice consumed in Ghana (100% of wheat) are imported (Cudjoe *et al.*, 2010). Rice alone costs the nation about $500 million yearly (Amikununo *et al*., 2013). The import of products such as poultry meat, vegetable oil, tomato paste and yellow corn is also on the rise in Ghana (Blay and Vijaya, 2016). Thus, any exchange rate depreciation is likely to increase not only petroleum price but food price in Ghana. As food prices increase, the welfare of consumers can be inimically affected since increasing food prices can erode their purchasing power and decrease their consumption. Higher food prices affect poor consumers the most, as they spend a comparatively higher share of their disposable income on food (Trostle, 2008).

Also, price volatility of food staples is one of the most complex factors affecting food security (Kalkuhl *et al.,* 2013). Recent food price crises have raised academic interest in improved volatility assessment. However, such assessments have only been restricted to developed economies. Literature on the relationship that exists among food price, petroleum price and macroeconomic fundamentals within the local context of a developing economy is non-existent (Serra, 2014).

In the light of this, the study assessed how sensitive food price is to changes in petroleum price and exchange rate in Ghana. To achieve this, the study first investigated the short run and long run relationships among food price, petroleum price and exchange rate in Ghana. It then analysed the impulse response of food prices to shocks in petroleum price and exchange rate in Ghana. Finally, it investigated the impact of petroleum price and exchange rate shocks on the volatility of food prices in Ghana.

2. Related literature

2.1. Modelling the linear relationship among economic variables

The Vector Autoregreesion (VAR) methodology is better suited for examining the long-run equilibrium relationship among different economic series because it better approximates the unknown model by taking dynamic interactions among the variables in the system into consideration (Phillips, 1991).

VAR models consist of dynamic systems of equations in which the present state of each variable in the system (in the case of this study, food price, petroleum price, exchange rate or interest rate) is explained by both past movements in that variable and all the other variables in the system (Stock and Watson, 1996). Juxtaposing this with preceding traditional models, fewer assumptions about the fundamental structure of the economy are made. The VAR models are characterised by some few assumptions like the nature of variables to include in the system and the choice of lag length to use (Ng and Perron, 2001). These can have important statistical and empirical implications. Nevertheless, the VAR approach is useful for exploring what a given theoretical view implies for the dynamic behaviour of the variables of interest. Thus, a benefit of the VAR approach is that it does not entail any strict economic theory within which the model is grounded (Enders, 1995). Rather, the VAR models are determined solely by the data used by deriving a good statistical representation of the past interactions between the economic variables (Phillips, 1991).

Another econometric issue associated with the estimation of VAR models is the problem of nonstationary time series. According to Engle and Granger (1987), if some of the variables (i.e. food price, oil price, exchange rate or interest rate) are nonstationary, the VAR would be liable to specification bias. This suggests that stationary and nonstationary processes must be analysed differently. According to Engle and Granger (1987), a linear combination of different nonstationary processes might yield a stationary process. This linear combination, which is called the cointegrating equation, is often interpreted as a long-run equilibrium relationship among the variables (Johansen, 1988). The cointegration analysis and VAR technique cannot only be used to model the long-run equilibrium relationship between non-stationary variables but also, their short-run disequilibrium adjustments (Johannson, 1988). These long–run relationships are usually hypothesized by economic theory, where the theory postulates the existence of an equilibrium relationship that relates the variables in question. The concept of cointegration is a statistical characterisation of a situation where the variables in the hypothesized relationship should not diverge from each other in the long run, or if they should diverge from each other in the short-run, this divergence must be stochastically bounded and diminishing over time (Banerjee *et al.*, 1993). It is essential to check for possible cointegration, because it determines the specification of the model to be used for causality testing (Sims *et al.*, 1990). According to the Engle–Granger Representation Theorem, if there is cointegration between the explained variable (food price) and the explanatory variables (petroleum prices, interest rate and exchange rate), then, there exists a valid error correction mechanism between the variables (Engle and Granger, 1987). As such, if the variables are cointegrated, then the Granger (1969) causality test would have to be based on a Vector Error-Correction Model (ECM) rather than on an unrestricted VAR model (Johansen and Juselius, 1990). However, if the variables are not found to be cointegrated, then the Granger (1969) causality test must be based on the VAR model (Chimobi and Igwe 2010).

2.2. Modelling the non-linear relationship among economic variables

VECMs only explain the behaviour of stochastic processes in their levels by assuming their variance to be constant over time. However, Obstfeld and Taylor (1997) have shown that price series cannot be analysed only in their levels due to their characteristic persistent volatility. According to them, nonlinearity in price behaviour should also be expected because changes in the political or economic structure of a nation can lead to structural breaks. To model volatility, the ARCH, GARCH and MGARCH models are commonly used to capture any time–changing volatility clustering and spill-over effects (Serra *et al*., 2011).

The ARCH models were introduced by Engle (1982) to allow for the variance–covariance matrix of residuals generated from a specified Conditional Mean Equation to be a function of the actual size of the lagged residuals in a Conditional Variance Equation. The capacity of the ARCH models to detect the presence of persistent volatility in stochastic processes was limited. This prompted the development of the generalized version by Bollerslev (1986). In this GARCH model, the variance–covariance matrix of the generated residuals was not only a function of the lagged error terms, but also its own lags. The major restriction of this model was its limited capacity to be specified with different functional forms. This led to the development of the multivariate forms. While the multivariate GARCH (MGARCH) models could be specified using different functional forms, they are too restrictive when it comes to allowing for volatility spill-overs across different markets (Nelson, 1991).

The BEKK–GARCH model which is a Conditional Variance Model specification by Baba–Engle–Kraft–Kroner, defined in Engel and Kroner (1995), and later in Kroner and Ng (1998), has emerged as a popular tool in the modelling of volatility in recent years. It has the flexibility of allowing some policy variables to be restricted as exogenous in order to test for their volatility causality links with an economic variable.

2.3. Food–Petroleum Price linear relationships

Baffes (2007) applied the OLS procedure to annual data from 1960 to 2005 to investigate how oil price affects 35 internationally traded commodities that included food. At the aggregate level, he found that the oil price pass–through to the non-energy International Commodity Index was 16 percent. At the disaggregated level, he found that the pass–through from oil prices to Fertilizers Index and Food Index were 0.33 and 0.18 respectively. Kwon and Koo (2009) also found oil prices as the key determinant of food prices. They applied the Toda-Yamamoto and Dolado-Lutkepohl (TYDL) Granger causality test to monthly data from January 1998 to July 2008 to investigate the relationship among food prices, the exchange rate and oil prices in the US. They reported that oil prices uni-directionally Granger caused food prices. This was later buttressed by Chen *et al.* (2010), who applied Autoregressive Distributed Lag Modelling (ARDL) to weekly frequency data from 1983 to 2010 to examine the relationship between crude oil prices and the international price of corn, soybeans and wheat. They reported that a percentage rise in oil price would globally lead to a 29.41, 155.50 and 41.30 percent increase in the prices of corn, soybeans and wheat respectively. Using a different approach, Saghaian (2010) applied the Vector Error Correction Model (VECM) and the Granger causality analyses to investigate the impact of petroleum prices on the prices of corn, soybeans and wheat using monthly data from 1996 to 2008. He found long–run equilibrium relationships among the petroleum, corn, soybean and wheat prices. He also reported that oil prices uni-directionally Granger caused all the food commodity prices.

Du *et al*. (2011) later reported that oil price shocks induce sharp changes in food prices; especially those of corn and wheat. They applied Stochastic Volatility with Merton Jump in Return (SVMJ) model to weekly data from 1998 to 2009 to investigate the relationship between food and petroleum prices. On their part, Ciaian and Kancs (2011) analysed the relationships between food and oil price from 1993 to 2010 and found that their interdependencies are increasing over time. Prices of food commodities were all having long–run equilibrium relationship with oil prices from 2005 to 2010, whereas little evidence of cointegration was found in the periods of 1993–1998 and 1999–2004.

After the 2011 food crisis, Nazlioglu and Soytas (2012) investigated the dynamic relationship between world oil prices and 24 agricultural commodity prices by employing the Panel Co-integration and the Granger Causality Techniques with monthly data from 1980 to 2010. They found food prices changes being Granger caused by crude oil prices changes. In the same light, and using data in monthly frequency from January 1990 to June 2013, Gozgor and Kablamaci (2014) studied the relationship among crude oil prices, the real effective exchange rate, global market risks and 27 agricultural commodity prices by employing the Panel-Wald Causality Test. The results reinforced the hypothesis of uni-directional causality running from oil prices and the real effective exchange rate to the commodity prices. Recently, Adammer and Bohl (2015) used monthly data from 1993 to 2012 by applying the Momentum Threshold Autoregressive Method (MTAR), the VEC model and the Granger causality analysis. The authors conclude that there is a bi-directional causality between the real oil price and the real exchange rate and that there is a uni-directional causality running from oil prices to wheat prices.

2.4. Food–Petroleum Price Volatility Links

Previous studies have revealed that the food–petroleum price nexus cannot only be analysed in their price levels due to the persistent volatility that normally characterises price time–series. Often in price time–series, episodes of high (low) volatility come after episodes of low (high) volatility and the Autoregressive Conditional Heteroscedastic (ARCH) models as well as their Generalized

(GARCH) and multivariate generalized versions are commonly used to capture this time changing volatility clustering and spillover effects (Serra *et al*., 2011; Zhang *et al*., 2009).

After the 2007–08 food crisis, Zhang *et al*. (2009) found price volatility links between oil, corn and soybean markets when they analysed the volatility spill–overs between U.S. ethanol, corn, soybean, and oil weekly prices by employing of the Baba–Engle–Kraft–Kroner (BEKK) modification of the GARCH model that was defined in Kroner and Ng (1998). Mutuc *et al*. (2010), on the other hand, employed monthly frequency data on prices of crude oil, cotton, soybeans, corn and wheat from 1976 to 2008 using Structural Vector Autoregression (SVAR) analysis. They found that the commodity prices were not responsive to global oil supply shocks although they respond to increase in the global oil demand.

Du *et al*. (2011) studied the impact of crude oil on corn and wheat futures prices between November 1998 and January 2009 using the Stochastic Volatility models. They found no spill–over effect before October 2006. They however found strong volatility spill–overs from the crude oil to corn markets between October 2006 and January 2009. Nazlioglu (2011) adopted the Toda-Yamamoto (TY) and the Disk- Panchenko (DP) causality analyses to evaluate the impact of crude oil prices on those of wheat, corn and soybeans, using weekly frequency data from 1994 to 2010. While the results of the linear causality analysis support the neutrality hypothesis, which suggests no causality between the oil and food prices, the results of the non-linear causality analysis suggest very strong uni-directional causality from oil to food prices.

Wixson and Katchova (2012) found an asymmetric relationship between food and crude oil prices. They explained that the magnitudes of responses of food prices to increases and decreases in oil prices are different. This was in line with Trujillo-Barrera *et al*. (2012) who applied a MGARCH model that incorporated an exogenous random shock coming from the crude oil market to examine the volatility interactions between U.S. corn, ethanol, and crude oil price. Their results suggested volatility spill–overs from crude oil to corn prices.

Also, using daily data from 1986 to 2011 and separating them into pre– and post– food crises groups, Nazlioglu *et al.* (2013) adopted the GARCH technique to investigate the existence of volatility spill over between the prices of crude oil, wheat, corn, soybeans and sugar. In the pre–crisis era, they reported no price volatility spill–over from oil to the food commodities. However, for the post-crisis period, they found a uni-directional volatility spill–over from oil to corn prices. They also found a bi–directional volatility spill–over between oil and soybeans as well as oil and wheat.

In a similar approach, Wang *et al.* (2014) also divided their monthly data covering the periods of 1980 to 2012 into two groups; the pre-crisis and the post-crisis. They employed the SVAR analysis to examine the effects of oil supply shocks, aggregate oil demand shocks and other oil–specific shocks on the prices of cocoa, soybean, barley, wheat, corn, cotton, rice, coffee and tea. They found oil price changes to have significant impact on the agricultural commodity prices in the post-crisis period than in the pre-crisis period.

2.5. Effect of Exchange Rates on Food Prices

By applying Granger causality analysis to data from Australia, Canada, Chile, New Zealand and South Africa, Chen *et al*. (2008) postulated that exchange rates can be used to forecast future commodity prices. To restrict this to general agricultural commodities, and to investigate the effect of petroleum prices and exchange rates on the domestic prices of US corn, cotton, soybeans, and wheat, the cointegration and the vector error correction analysis results of Harri *et al*. (2009) found substantial long run equilibrium relationship between all the selected agricultural prices (except wheat) and oil prices. They reported that exchange rate is a key determinant of agricultural prices. Narrowing the relationship further down to food commodities, and using oil prices, exchange rate, and food prices from January 1998 to July 2008, Kwon and Koo (2009) employed the Granger causality test of Toda and Yamamoto (1995). The results of the study uncovered exchange rate and oil price as prime determinants of food prices through various channels. Their results were consistent with Baek and Koo (2010) who also found exchange rate as a major determinant of food prices. Baek and Koo (2010) found exchange rate as one of the major short-term and long-term determinants of food prices in the U.S. from January 1989 to January 2008. They also reported that petroleum prices have insignificant impact on food prices in the short–run although the reverse was identified in the long–run. On the part of Frank and Garcia (2010), they divided their sample into two groups in order to uncover the relationship among oil prices, exchange rates and food prices. They employed the VAR model to analyse the weekly data from 1998 to 2006. For the second group ranging from 2006 to 2009, VEC model was used. Their findings further confirmed that the impact of oil prices and exchange rates on the food prices is significant and the intensity of this impact is immense between 2006 and 2009 than between 1998 and 2006.

2.6. The Impact of Other Macroeconomic Factors on Food Price Volatility

Gilbert (2010) revealed that other macroeconomic variables such as the growth in the global economy and monetary expansion together with petroleum prices and exchange rate have a causal impact on the prices of food between 1969 and 2008. In his quest to investigate this revelation further, Balcombe (2011) applied a random parameter model with time changing volatility that allowed the incorporation of exogenous variables, like interest rates, exchange rates, yields and stock levels in the conditional variance equation. Using the prices of a variety of cereals, vegetable oils, dairy products, and meat products, his results reinforced the hypothesis that volatility in petroleum price has a positive impact on food price volatilities. He also reported that Interest rates, Exchange rates, Yields and Stock levels have a very significant impact on price volatility of food. Also, using a bivariate GARCH model with time changing volatilities and an incorporation of exogenous shock variables such as Interest rates and Stock levels, Serra and Gil (2012) found that stock levels reduce food price fluctuations. Their findings also concluded that volatilities in interest rate accelerate higher volatility in food prices.

3. Data and Methodology

3.1. Data

The data used in this article are food price indexes (2012 as base year), the domestic ex-pump price for petrol and the interbank dollar exchange rate. Changes in interest rate may also affect food price. Therefore, in addition to the petroleum price and exchange rate, interest rate is included as one of the control variables in the model. The Bank Lending Rate is adopted as proxy for interest rate.

The food-CPI data was taken from the Ghana Statistical Service. The data on domestic Ex-pump price for petrol was obtained from National Petroleum Authority in Ghana. The exchange rate and interest rate data were collected from the Bank of Ghana. The monthly data was constructed by simply taking the average value of all observations in each month.

The monthly frequency data spans from January 1997 to August 2017. This sample which spans a period of twenty-one years which includes a period of dramatic collapse of the world economy during global financial crisis in 2008/09 and its subsequent recovery as well as the 2007/08 and 2010/11 global food crises.

3.2. Stationarity Test

Studies that employ time series analysis usually use a stream of data from the past to examine historical relationships, such that if the analysis is statistically well grounded, then the uncovered historical relationship can be used to forecast the future. It is therefore important that time series variables follow at least a stochastic process and be stationary (Fuller, 1976).

While the problem of unit root can be identified by a pictorial inspection of the series of the variable in question, statistical tests are better employed to detect this nuisance. Prominent among these tests are the Augmented Dickey–Fuller (ADF) and Phillips-Perron (PP) tests.

According to Dickey and Fuller (1979), the test is constructed by regressing the first difference of the variable onto its own lagged value and the lagged values of its first differences. Using the food price series, the ADF test uses the following general model to examine unit root:

$$\Delta FP_t = \beta_1 + \beta_2 t + \delta FP_{t-1} + \sigma\sum_{t-1}^{m} \Delta FP_{t-1} + \varepsilon_t$$

Where

- FP_t is the dependent variable (food price at time *t*);
- *t is* a time trend;
- Δ is the differencing operator; and
- ε_t is a white noise process.

The ADF coefficient, δ, is then tested to be either zero or not.

Thus, from the above equation,

$H_0 : \delta = 0$ (FP_t is non-stationary or has a unit root)

$H_1 : \delta < 0$ (FP_t is stationary or has no unit root)

This same analogy applies for the Phillips-Perron test. As an advantage, the PP test applies a correction mechanism that estimates the long run variance of the residual series with a variant of the Newey–West formula to correct possible serial correlations in errors. This makes the PP test a more powerful alternative than the ADF test in principle.

Although the problems associated with unit roots can be solved by either taking the log or differencing the time series variables (Solo, 1984), they can be evaded completely by employing the concept of cointegration (Stock, 1987).

3.3. Cointegration Test

While a unit root test tells us the number of times a variable would to be sequentially differenced until it becomes stationary, a cointegration test tells us whether there exist long–run theoretical relationships among the variables under study (Engle and Yoo, 1991). The Johansen (1991) cointegration procedure is adopted to investigate the existence of a long-run relationship (co-integration vector) among the price series in this study. The Johansen procedure examines a vector autoregressive (VAR) model of FP_t written in error-correction form; $\Delta FP_t = \sum_{i=1}^{p-1} \Gamma_i \Delta FP_{t-i} + \prod FP_{t-1} + \mu_t$

where, Γ and ∏ are matrices of parameters (Johansen and Juselius, 1990). *P* is the lag length selected on the basis of Schwarz information criterion.

To determine the cointegrating rank, Johansen (1991) proposes two possible likelihood ratio tests: the Maximum Eigenvalue (λ_{max}) test and the Trace test.

The λ_{max} test is obtained using;

$LR(r_0, r_o + 1) = -T \ln(1 - \lambda_{r+1})$

H_o: the rank ($\prod$) = r_0

H_a: the rank ($\prod$) = $r_o + 1$

The Trace test is obtained using;

$LR(r_0,n) = -T \sum_{i=r+1}^{n} ln\,(1 - \lambda_i)$

H_o: the rank ($\prod$) = r_0

H_a: $r_0 < \text{rank} \leq n$

where n is the maximum number of possible cointegrating vectors.

The presence of at least one cointegrating relationship is necessary for the analysis of long-run relationship of the variables to be plausible.

3.4. The Empirical Model

Estimating the long-run and short-run magnitude and direction

The study would check for Error Correction in order to verify if the adjustment parameter is negative (Sims *et al.*, 1990), implying that the estimated equation is a valid Error Correction Model which then would be used to check the speed with which the system adjusts to equilibrium whenever there is departure.

The dependent variable is the log change in food price, and all the explanatory variables are lagged. The VECM is specified as;

$\Delta lnFP_t = \alpha_i + \sum_{i=1}^{n} \beta_i \Delta FP_{t-i} + \sum_{i=1}^{n} \gamma_i \Delta PP_{t-i} + \sum_{i=1}^{n} \theta_i \Delta RER_{t-i} + \sum_{i=1}^{n} \pi_i \Delta RIR_{t-i} + \delta_F lnFP_{t-i} + \delta_P lnPP_{t-i} + \delta_E lnRER_{t-i} + \delta_R lnRIR_{t-i} + \mu_i + \lambda\varepsilon_{t-1}$

Where λ is the speed of adjustment

- ε_{t-1} is the error correction term in t-1, and is specified as;
- $\varepsilon_{t-1} = lnFP_{t-1} - \eta lnPP_{t-1} - \varphi lnRER_{t-1} - \xi lnRIR_{t-1}$
- The coefficients in the error correction term are η, φ and ξ.
- η, the coefficient of petroleum price, explains by how much food price will change due to a percentage change in petroleum price.

- φ, which is the coefficient of exchange rate, explains the percentage change in food price as exchange rate changes by one per cent.
- Finally, the coefficient of interest rate is ξ, and it explains the percentage change in food price when interest rate changes by one per cent.
- The signs of η, φ and ξ explain the long run relationship each variable has with food prices.
- β, γ, and θ represent the short run price dynamics.
- Also, lnFP is the log of Food Price Index, lnPP is the log of domestic petroleum ex-pump price, lnRER is the log of real exchange rate, and lnRIR is the log of real interest rate.
- The error term, μ_t is assumed to be independently and identically distributed with N (0, 1).

Analysing the Impulse Response of Food Price

According to Goodwin and Pigot (2001), the nonstationarity of price data and error correction properties may allow shocks to elicit responses that are temporary (such that there is a return to the initial time path of the variables) or permanent (such that there is persistent shift in the time path). Impulse response functions (IRFs), which measure the impact of a unit shock to an endogenous variable on itself or on another endogenous variable (Naka and Tufte, 1997), is adopted to uncover the response of food prices to a unit shock in petroleum prices and exchange rates in Ghana.
Here, the response to a price shock is dependent on the history of the time series, as well as the sign and magnitude of the postulated shock in model.

Investigating the impact of petroleum price and exchange rate shocks on the volatility of food prices

This study employs Kroner and Ng (1998) specification of the Baba–Engle–Kraft–Kroner (BEKK) (1995) Conditional Variance Model to capture the presence or otherwise of price volatility across food prices in Ghana.

The BEKK–GARCH model is specified here as:

$H_t = CC' + A' u_{t-1} u_{t-1}' A + B' H_{t-1} B$

Where;

- H_t is the variance-covariance matrix,
- A, B, and C are parameter matrices that depict the volatility process.
- Matrix A is the ARCH effect denoting the effect of market innovations on the volatility process
- Matrix B is the GARCH effect representing the effect of previous volatility on existing volatility
- C is a lower triangular matrix comprising the exogenous variables in the model such as petroleum price, exchange rate and interest rate.
- u_t is the vector of errors from the conditional mean model.

The log likelihood function for the BEKK–GARCH model is;

$l_t = -\left(\frac{1}{2}\right) \sum_{t=t+1}^{t} log\ |Ht| - \left(\frac{1}{2}\right) \sum_{t=t+1}^{t} et'\ H_t^{-1} e_t$

where l_t is then maximized with respect to the parameter matrices A, B, and C.

H_o: Parameters in matrices A and B are equal to zero

H_a: Parameters in matrices A and B are not equal to zero

There is evidence of time varying volatility if the null hypothesis is rejected.

4. Results

To better capture the interactions between the price series during periods of extreme food price hike, and following Frank and Garcia (2010), Ciaian and Kancs (2011), Du *et al*. (2011), Nazlioglu *et al.* (2013) and Wang *et al.* (2014), the data was divided into five *time–periods*. This is because Stock and Watson (1996) have shown that most time series data are vulnerable to multiple structural breaks which are believed to play a major role in empirical failures. Hannan (1970) also suggested that such structural breaks might originate from steady shifts in the production process, disruptions in production due to political turmoil, globalization trend, and other exogenous shocks. Therefore, the study conducted a test for structural breaks to determine indeed the data should be divided into sub-samples. The exogenously determined breakpoints were adopted from Tadesse *et al.*, (2014). The period from January 1997 to December 2006 is considered as the *Pre–Food–Crisis Period*. The *First Food Crisis Period* covers January 2007 to September 2008. The *Post First Food Crisis Period* then covers October 2008 to July 2010. The period from August 2010 to December 2011 is the *Second Food Crisis Period*. The final *time–period* is the *Post Second Food Crisis Period* which extends from January 2012 to August 2017.

The Chow Test results for structural breaks are presented in **Appendix E**. The null hypothesis of no structural breaks at the exogenously specified breakpoints of January 2007, October 2008, August 2010, and January 2012 is rejected at the 1% significance level. This result suggests that the data stream can be divided into the five sub-samples**.** Test for difference in the mean of food price index for the various time periods are also presented in **Appendix A**. The result rejects the null hypothesis of no difference in mean (same mean) between the various time-periods. This further supports the disaggregation of the data into different sub-samples.

Examination of the Stationarity Properties of the Variables

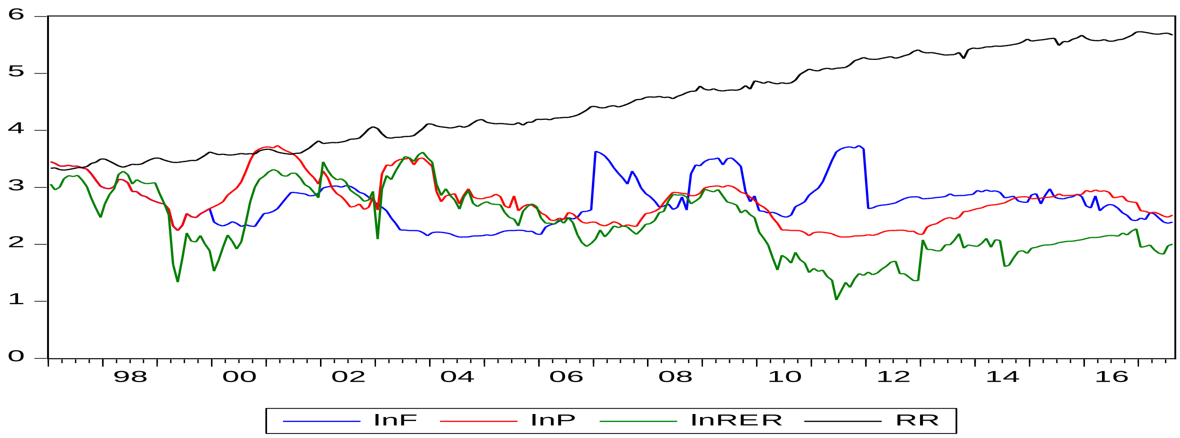
The stationarity properties of the variables used in this study are examined in this section. These include the use of a graphical approach before a formal test was conducted.

From figure 1, it is clear that none of the variables is stationary in before first differencing. However, the graphs suggest that the variables used in this study have intercepts. This indicates that the unit root equations used for the test must contain intercept terms.

In contrast, figure 2 shows that all the variables are stationary in their first difference. This is an indication that all the variables are Integrated of Order One and so their linear combinations may suggest the existence of long run relationships.

The results from the ADF and the Philip-Perron unit root tests are presented in **Appendix B**. For all the periods under investigation, the results indicate that at the 5% significance level, all the variables are not stationary before first differencing, confirming the result from the graphical presentation from Figure 1. Unit root tests are then conducted on the first difference of the variables to check if they will be stationary at their first difference.

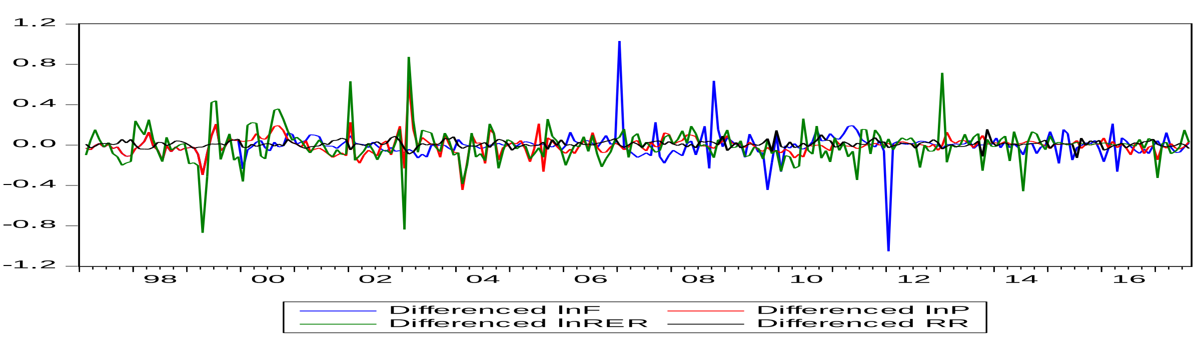
Figure 1: Graph of level variables (1997-2017)



Source: Constructed from BoG, GSS & NPA data

The results indicate that the growth rate of food price index is stationary at first difference according to both the Augmented Dickey-Fuller and Phillips-Perron tests. The implication is that the null hypothesis of presence of a unit root is rejected at 1% significance level and concludes that food price level (FP) is Integrated of Order One.

Figure 2: Graph of differenced variables (1997-2017)



Source: Constructed from BoG, GSS & NPA data

Note: LNF is the log of Food Price Index, LNP is the log of petroleum price, LNRER is the log of real exchange rate, and RR is the log of real interest rate

Similarly, petroleum price was found to be stationary and is Integrated of Order One. Exchange rate is also difference stationary. That is, after first difference, the variable became stationary. The null hypothesis of the presence of a unit root was rejected at the 1% significant level, thus leading to the conclusion that the variable is Integrated of Order One. Lastly, interest rate is also significant at 1% after first differencing. Both the ADF and the Philip-Perron tests suggest that the variable does not contain a unit root. The variable is stationary at first difference.

Therefore, all the price series in all the *time–periods* become stationary after first-differencing. Hence, it is concluded that the univariate representation of each of the four variables for all *time–periods* is characterized by unit root nonstationarity and each series is Integrated of Order One. An appropriate econometric technique to be used in this situation is cointegration analysis.

Cointegration Results and Analysis

The results of the Trace and Maximum Eigenvalue statistics of the Johansen cointegration test are presented in **Appendix C**.

Both the Trace and Maximum Eigenvalue test statistics indicate the presence of cointegration among the variables. For the *pre–food crisis* period, the null hypothesis of no cointegration is rejected by both the Trace and Maximum Eigenvalue tests. The Trace test further rejects the second null hypothesis of at most one cointegrating equation. Thus, the Trace test indicates two cointegrating equations at the 0.05 level but the Maximum eigenvalue test indicates one cointegrating equation at the 0.05 level. For the *first crisis* and *post second crisis* periods, the null hypothesis of no cointegration is rejected by both the Trace and Maximum–Eigenvalue tests with both tests indicating one cointegrating equation.

Similarly, the null hypothesis of no cointegration as well as that of at most one cointegrating equation are rejected by both the Trace and Maximum Eigenvalue tests for the *post first crisis* and *second crisis* periods. Therefore, both tests indicate two cointegrating equations for the two periods.

The Vector Error Correction Model Results and Analysis

An error correction model is then formulated after the unrestricted cointegration rank test. The idea behind such a model is the need to recover the long-run information lost from differencing the variables (Enders, 1995). The error correction model rectifies this problem by introducing an error correction term (ECT). This term is derived from the long-run equation based on economic theory and enables the measurement of the speed of adjustment of FP to its long-run equilibrium. It gives us the proportion of disequilibrium errors accumulated in the previous period that are corrected in the current period. The results of the VECM are reported in **Appendix D.**

Long run relationship

Thus, the long run effect of petroleum price and exchange rate on the food price level can be examined. The negative sign of the adjustment terms combined with their statistical significance is in compliance with the necessary condition for long run convergence in the VECM (Sims *et al.*, 1990).

The Error Correction Terms (ECTs) from the VECM results in **Appendix D** are summarised in equations 1-5 below. At long-run equilibrium, ECT=0. This implies that;

FP = 0.94*PP + 0.82*RER + 0.08*RIR ………………. (1)

FP = 1.93*PP + 2.12*RER + 1.10*RIR ………………. (2)

FP = 0.85*PP + 3.22*RER + 0.09*RIR ………………. (3)

FP = 1.42*PP + 4.38*RER + 1.10*RIR ………………. (4)

FP = 1.10*PP + 1.06*RER + 0.01*RIR ………………. (5)

Where equations 1, 2, 3, 4, and 5 represent the long–run relationship among the price series for the *Pre–Food–Crisis*, the *First Food Crisis*, the *Post First Food Crisis*, the *Second Food Crisis* and the *Post Second Food Crisis* periods in Ghana respectively.

Since the variables were log-transformed prior to estimation, the estimated coefficients are elasticities.

The results from the cointegration analysis as well as the VECM indicate a positive relationship between petroleum price and food price levels at all times. The results indicate that, for all times, petroleum price increases result in increases in the food price level. Petroleum price is an important variable in explaining the changes in the Food Price Index in Ghana in the long run. The variables are found to be statistically significant at 1%. The positive effect of petroleum price is consistent with the studies of Nazlioglu and Soytas (2012), Gozgor and Kablamaci (2014), as well as Adammer and Bohl (2015) who found a positive impact of oil price changes on food price changes. According to equations 1-5, an increase in petroleum price by 1% would result in an increase in the Food Price Index by 0.94%, 1.93%, 0.85%, 1.42%, and 1.10% for the *Pre–Food–Crisis*, the *First Food Crisis,* the *Post First Food Crisis,* the *Second Food Crisis* and the *Post Second Food Crisis* periods in Ghana respectively. This implies that relationship between food and petroleum prices in Ghana was elastic during the two food crises periods as well as the post second food crisis period. The results further indicate that food prices in Ghana are very sensitive to petroleum prices during periods of global food crisis that are exacerbated by surges in crude oil prices.

This is because the food price response of petroleum price was highest during the first and second food crises. Farmers and other food producing firms use petroleum products to fulfil their transportation and other operational needs since they mostly use petroleum as a fuel for their machines used in production. The bulky nature of agricultural product increases their transportation cost. Also, chemical fertilizer such as urea, which is a critical input of agricultural production, is also a petro-derivative. Thus, any abrupt surge in petroleum prices would lead to increased cost of production. This increase in production costs would then translate into higher food prices since producers would not totally bear the spike in costs.

When compared with various other studies, the results suggest a rather small effect of oil prices on food prices in Ghana. For example, Baffes (2007) found that a percentage increase in oil price would lead to an 18% increase in the Food Price Index of major global food producers. Chen *et al.* (2010) also found that a 1% increase in oil price would lead to a 29.41, 155.50 and 41.30 percent increase in the prices of corn, soybeans and wheat respectively in US. This relatively smaller effect could be due to the fact that, for a country like Ghana, government has been subsidizing petroleum products. Therefore, increases in oil prices on the world market may not be fully reflected in domestic petroleum prices.

The study examined the effect of exchange rate on food price levels. The result showed that exchange rate depreciation had a positive and significant relationship with food price in the long-run. The result indicates that a depreciation of the cedi by 1% results in an increase in the Food Price Index by 0.82%, 2.12%, 3.22%, 4.38%, and 1.06% for the *Pre–Food–Crisis*, the *First Food Crisis*, the *Post First Food Crisis*, the *Second Food Crisis* and the *Post Second Food Crisis* periods in Ghana respectively. This implies that the relationship between food price and exchange rate in Ghana have been positive and elastic after the first food crisis period of 2007/08. The results further show that, the exchange rate sensitivity of food price in Ghana was much stronger during the first and second food crises periods.

Food prices in Ghana have been very sensitive to exchange rate during these periods because there is an increase in the imports of food products (such as rice, poultry meat, vegetable oil, tomato paste and yellow corn) within this period (Blay and Vijaya, 2016), with rice alone costing the nation about $500 million yearly (Amikununo *et al*., 2013). The situation is further exacerbated by rampant exchange rate depreciation which is primarily caused by the dynamics in the petroleum sub-sector. This is because as a petroleum dependent country who imports crude oil to supplement domestic supply, any increase in crude oil price on the world market would create current account deficit which would eventually lead to exchange rate depreciation. This may have increased the cost of food imports. This can also lead to an increase in the cost of imported inputs used in food production. The overall impact of this phenomenon would be the collective increase in food prices. This result is consistent with the findings of Baek and Koo (2010), Frank and Garcia (2010), Gozgor and Kablamaci (2014), as well as Adammer and Bohl (2015) which found a positive relationship between food price changes and exchange rate.

The effect of interest rate on food price is positive. Interest rate is found to be significant and positively related to food price levels in the long run. A 1% increase in interest rate would result in a 0.08%, 1.10%, 0.09%, 1.10% and 0.01% increase in food prices for the *Pre–Food–Crisis*, the *First Food Crisis*, the *Post First Food Crisis*, the *Second Food Crisis* and the *Post Second Food Crisis* periods in Ghana respectively.

This implies that, the relationship between food prices and interest rate in Ghana was elastic only during the two food crises periods. As interest rates increase, the cost of borrowing by firms increases. Consequently, the total amount of money borrowed by food producers and processors would decrease, which would subsequently decrease the amount of money available for food production. This may decrease the scale of food production and distribution or increase the cost of food production which will increase food prices.

Short run dynamics

The error correction mechanism provides a means whereby a proportion of any disequilibrium in the current period is corrected in the next period. This is so that it reconciles the long-run and short-run behaviours among the variables under investigation.

The error correction terms reflect the temporal status of the long-run relationship in the system. The signs and sizes of their coefficients reflect the direction and speed of adjustment from the short-run disequilibrium to long-run equilibrium state. According to the results of the VECM in **Appendix D**, all the variables have their expected signs, including the error correction terms. The speeds of adjustments (λs) are all statistically significant at 1 % and have the right sign (negative sign) which reconfirms the presence of cointegration in this system. In other words, the significant negative value of adjustment terms (λs) at 1% level implies that food prices, petroleum prices and exchange rate tend to converge in the long run in Ghana and that exchange rate, and that petroleum prices tend to explain changes in food prices. This also implies that any disequilibrium in the short run due to shocks could be adjusted in the short run or corrected completely in the long run.

The results show that the speed of adjustments of change in food price to the long run equilibrium path are -0.1021, -0.2525, -0.1483, -0.8849, and -0.1454 for the *Pre–Food–Crisis,* the *First Food Crisis,* the *Post First Food Crisis*, the *Second Food Crisis* and the *Post Second Food Crisis* periods in Ghana respectively. The significant coefficients of the error correction terms imply that whenever the actual value of food price falls below the value consistent with its long-run equilibrium relationship, changes in petroleum price, exchange rate and interest rate help bring it back to the long-run equilibrium value. This is done at the rate of the size of these coefficients or speed of adjustment.

The short-run impact of petroleum price on food price in Ghana is positive and significant at the 5 % level in the First Crisis Period. The estimated figure suggests that, ceteris paribus, a 1 % rise in petroleum price will cause a deviation from the long-run equilibrium relationship during the current month by causing food price to increase by 0.73%. A comparatively higher magnitude of 1.24% was recorded for the response of food prices to a 1% exchange rate depreciation for the same period. This disequilibrium is eliminated at a rate of 25% in each subsequent month until the markets completely readjust unto their long run steady state or equilibrium path. This speed of adjustment is low since it is further away from unity (Sarker and Jaramillo-Villanueva, 2007). The Second Food Crisis Period recorded the highest speed of adjustment of 89%. Thus a 1% increase in petroleum price and real interest rate inflates food prices by 0.83% and 0.44% respectively with a comparatively higher magnitude of 1.23% due to exchange rate depreciation. This suggests that food prices in Ghana adjust faster during periods of high petroleum prices and real exchange rate depreciation than periods of low. This may be attributed to the various short-term emergency response strategies that are implemented during such times. This includes the ban on foreign currency transactions during the severe exchange rate depreciation in 2015, and the removal of some fuel taxes and levies during petroleum price spikes in 2017.

Impulse Response Analysis

To obtain additional insights into the transmission mechanisms among food prices, petroleum prices and exchange rate, impulse response functions (IRFs) were computed. The impulse response function gives additional information about the long-run dynamic interrelationships among the price variables such as the time path needed to take the system back to equilibrium. Impulse response function is designed to track the responsiveness of endogenous variables in the VECM system after a single shock from one or more disturbance terms is applied to each variable at the various periods (Naka and Tufte, 1997). It also gives some information on the time it takes for the response of food prices to a unit shock in the petroleum price and exchange rate to be eliminated from the market.

The graphs of the response of food prices to Cholesky one standard deviation positive shock on the innovations of exchange rate, petroleum prices and interest rate for the *Pre–Food–Crisis*, the *First Food Crisis*, the *Post First Food Crisis*, the *Second Food Crisis* and the *Post Second Food Crisis* periods in Ghana are presented in **Appendix F**. For the sake of brevity, only the first 10 months are paid attention.

An inspection of the graphs reveals that the Impulse Response analyses are in conformity with the long run results. The response of food price to a one standard deviation positive shock in petroleum price, exchange rate and interest rate is positive at all *time–periods*. A one standard deviation positive shock in petroleum price would increase food price steadily at all times. The response was intense in the two food crises periods where the rise was sharper and the effect did not decay even 10 months after the shock. Similar patterns can be observed in the response of food prices to a shock in exchange rate. Expectedly, the response of food price to a one standard deviation positive shock in interest rate is immediately negative during the crisis–free periods but increases steadily about three months after the shock to become positive although the responses are not significant. In the food crisis periods, however, the response of food prices to a one standard deviation positive shock in interest rate is positive throughout the duration and the effect is does not die out even 10 months after the shock.

An Examination of Volatility in Food Prices in Ghana

The VECM results explain price behaviour in their levels by explicitly allowing for nonstationarity and cointegration based upon the fairly simplifying assumption that price variance is constant over time.

However, Abderabi and Serra (2015) have shown that invariant price variance should not be expected. This is because prices usually exhibit volatility that tends to change over time. To capture time changing volatility in food prices in Ghana from January 1997 to August 2017, the BEKK-GARCH model specification was used. This specification is in two parts; the Conditional Mean Specification and the Conditional Variance Specification. The Conditional Mean Equation of the volatility of food prices is modelled as MA(1) to account for the first-order serial correlation in food prices.

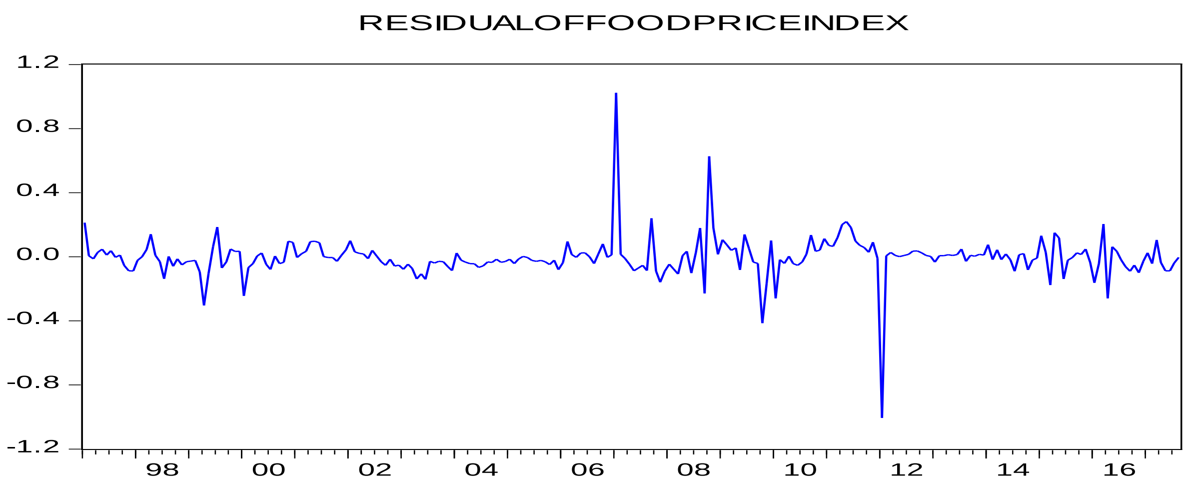
Thus, in the first sub–model, the Conditional Mean Equation was estimated using ARMA–Least Squares procedure and the residuals were generated. The graph of the residuals as presented in figure 3 was then examined to determine whether or not the ARCH/GARCH procedure can be used.

From figure 3, periods of high volatility prior to year 2000 are followed by periods of relatively low volatility from year 2000 to 2007. This is then followed by periods of high volatility from year 2007 to 2012. This was then followed by periods of low volatility from year 2012 to 2015. The periods between year 2015 and 2017 exhibited relatively high volatility.

It can therefore be deduced that food prices in Ghana exhibit *time–changing volatility* characterised by periods of low volatility following periods of high volatility, which are then followed by periods of low volatility and then periods of high volatility. Food price shows periods of wide swings for some time period and periods of rather moderate swings in other time periods, thus exemplifying the phenomenon of volatility clustering. This suggests that food prices in Ghana follow a GARCH process (Bollerslev, 1986).

To validate the choice of the GARCH procedure, the residuals were statistically tested for the presence of ARCH effect (*time–varying variance*) in the food price data. The result of the LM ARCH test is presented in table 1.

Figure 3: Graph of the residuals from the conditional mean equation



The result rejects the null hypothesis of no ARCH effects since the probability value shows that ARCH effect ($RESID_{(-1)}^2$) is significant at 1% significance level. This satisfies the pre–condition for introducing the ARCH/GARCH procedure. In other words, the ARCH LM test was conducted and evidence of ARCH effects was found, thus supporting the use of a GARCH model. This paved the way for the introduction of the Conditional Variance Estimation.

Table 1: Results of LM ARCH test for volatility clustering

Variable	Coefficient	Std. Error	t-Statistic	p-value
C	0.0015**	0.0007	2.0754	0.0390
ARCH effect	0.2903***	0.0611	4.7480	0.0000

Source: Author's estimate

The Conditional Variance Equation was modelled as a linear function of past squared residuals (ARCH component) and past conditional variances (GARCH component) (Bollerslev, 1986). Thus, in the second sub–model, the Conditional Variance Equation was estimated with food price volatility as the dependent variable whilst the petroleum prices, exchange rate, and interest rate were assumed to be exogenous. The results of the Maximum Likelihood estimates of the Conditional Variance Equation under the assumption of Normal Gaussian Distribution are presented in table 2.

From table 2, the ARCH effect ($RESID_{(-1)}^2$) is significant at the 1% significance level. This means that past shocks or innovations in food prices in Ghana positively influence current volatility in food prices. This implies that any unanticipated event or error that will cause food price spike at a particular time in Ghana is likely to have a long-lasting effect in the food market. Such shocks would trigger food price volatility in the future.

Table 2: Results of conditional mean and conditional variance estimation

Variable	Coefficient	Std. Error	z-Statistic	p-value
C	0.9135***	0.1824	5.0074	0.0000
AR(1)	1.0000***	1.27E-05	78831.94	0.0000
Estimates of variance equation				
C	0.0612***	0.0217	2.8182	0.0048
ARCH effect	0.4474***	0.0808	5.5382	0.0000

GARCH effect	0.4222***	0.1400	3.0152	0.0026
RER	0.4364***	0.1214	3.5949	0.0000
PP	0.4055***	0.1147	3.5351	0.0000
RIR	0.0014***	0.0004	3.2814	0.0010
R-squared		0.9949		
Adj. R-squared		0.9948		
Durbin-Watson stat		1.9828		

Note: FP is the log of Food Price Index, PP is the log of petroleum price, RER is the log of real exchange rate, and RIR is the log of real interest rate.

The GARCH effect ($GARCH_{(-1)}$) is also significant at the 1% significance level implying that past volatility in food prices impacts positively on current volatility in food prices. Any shock in food market may stimulate ripple effects in food prices that can be either positive or negative depending on the nature of the shock. This implies that such shocks can generate volatility in food prices. This volatility can also generate further volatility in the future. This also means that instability of food prices in previous years serve as an indicator of the pathway of possible price movement of food items in the future. Therefore, food prices have the highest probability to undergo larger and frequent price changes in the future due to the fact that both past mistakes and past volatilities influence current volatility.

It can also be deduced from the results that shocks whose sources are not from the food market, or outside shocks also influence volatility in food prices in Ghana. Such shocks may stem from exchange rate, petroleum prices and interest rate fluctuations. Exchange rate was significant at the 1% significance level. Any 1% depreciation in exchange rate would lead to a 0.44% increase in food price volatility in the current period. Also, at the 1% significance level, a 1% increase in petroleum prices would increase volatility in food prices by 0.41%. Finally, at the 1% significance level, a 1% increase in interest rate would increase volatility in food prices by 0.0014%.

These findings are consistent with Balcombe (2011) as well as Serra and Gil (2012) who found exchange rate, oil prices and interest rate to be exogenous influences whose increase accelerates volatility in food prices.

The constant term in the variance equation is positive and significant at the 1% significance level. This implies that the model is well-specified.

Also, the closeness of the sum of the coefficients of the ARCH and GARCH effects to unity implies that food price volatility shocks in Ghana are persistent. This means that a shock in a given period will persist for many periods in the future.

Conclusion

The positive relationship among food price, petroleum price, exchange rate and interest rate indicate that any increase in petroleum price and interest rate together with exchange rate depreciation contributes to food price increases in Ghana. Food price was found to be elastic to petroleum price in the two food crises periods and ever since. Food price was found to have been elastic to exchange rate deprecation since the first food crisis period of 2007/08. However, food price was only found to be sensitive to interest rate during the two food crises periods. The magnitude of the elasticity values implies that petroleum price increases, exchange rate depreciation and interest rate increases in Ghana contributed significantly to the food price surges in 2007/08 as well as 2010/11 crises. Petroleum price increases and exchange rate depreciations are still contributing significantly to food price increases in Ghana. Interest rate however, seems pretty insignificant in explaining food prices before and after the food crises periods. The response of food prices to unanticipated shocks in petroleum price, exchange rate and interest rate is positive, and the impact of such shocks does not decay even after 10 months. This shows that any increase in food prices resulting from petroleum price increases and exchange rate depreciation is likely to be persistent for a long time.

Also, since food price volatility was found to be positively affected by its own past shocks (its own ARCH effect) and past volatility (its own GARCH effect), it implies that instability in food prices during previous years serve as an indicator of the pathway of possible price movement of food items in the future. Therefore, food prices in Ghana have the highest probability to undergo larger and frequent price changes in the future. Volatility in food prices is not only influenced by family shocks (its own ARCH and GARCH) but exogenous shocks such as exchange rate depreciation, petroleum prices increases and interest rate increases. In addition, food price volatility shocks in Ghana are persistent. This means that a shock in a given period will persist for many periods into the future.

It is recommended that policy aimed at food price stabilization must build national petroleum buffer stocks to stabilize fuel prices, improve exchange rate and interest rate management, build district, regional and national food buffer stocks and selectively target fuel subsidy at crop farmers and food processors, and remove bottlenecks in food marketing.

REFERENCES

Abdelrabi, F., & Serra, T. (2015). Food–energy nexus in Europe: Price volatility approach. *Energy Economics*, *48*(1), 61–85.

Adämmer, P., & Bohl, T.M. (2015). Speculative bubbles in agricultural prices. *Review of Economics and Finance*, 55(1), 67–76

Amikuzuno, J., Issanaku, G., & Daadi, E. B. (2013). Price transmission between imported and local rice markets in a liberalised economy: Are Ghana's rice wars just much I do about nothing? *Journal of Economics and Sustainable Development*, *4*(20), 109–119.

Baba, Y., Engel, R. F., Kraft, D. F., & Kroner, K. F. (1995). Multivariate simultaneous Generalised ARCH. *Econometric Reviews*, *15*(1), 205-255.

Baek, J., & Koo, W.W. (2010). Analysing factors affecting U.S. food price inflation. *Canadian Journal of Agricultural Economics*, *58*(1), 303–320.

Baffes J. (2007). *Oil spills on other commodities* (Paper No. 4333). World Bank Policy Research Working Paper. The World Bank.

Balcombe, K. (2011). The nature and determinants of volatility in agricultural prices: An empirical study. In: Prakash, A. (ed.), *Safeguarding Food Security in Volatile Global Markets* (pp. 85–106). FAO, Rome.

Banerjee, A., Dolado, J.J., Galbraith, J.W & Hendry, D.F. (1993). *Co-integration, error correction, and the econometric analysis of non-stationary data.* Oxford, England: Oxford University Press.

Blay, J. K., & Vijaya, K.R. (2016). Market integration between selected imported rice markets in Ghana. Application of non-linear co-integration approach. Research Journal of Agriculture and and Forestry Science, 4(2), 1-7.

Bollerslev, T. (1986). Generalised Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics*, *31*(3), 307-27.

Chen, S., Kuo, H., & Chen, C. (2010). Modelling the relationship between the oil price and global food prices. *Applied Energy*, *87*(1), 2517–2525.

Chen, Y., Rogoff K., & Rossi B. (2008). *Can exchange rates forecast commodity prices?* (Paper No. 94). Working Paper for Economic Research Initiatives at Duke (ERID). Duke, England.

Chimobi O.P., & Igwe O.L. (2010). Budget deficit, money supply and inflation in Nigeria. *European Journal of Economics*, 19(2), 1450–2887.

Ciaian, P., & Kancs, A. (2011). Interdependencies in the energy–bioenergy–food price systems: A cointegration analysis. *Resource and Energy Economics*, 33(3), 326–348.

Cudjoe, G., Breisinger, C., & Diao, X. (2010). Local impacts of a global crisis: Food price transmission, consumer welfare and poverty in Ghana. *Food Policy*, 35(4), 294–302.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of estimators for autocorrelated time series with a unit root. *Journal of American Statistical Society*, 74(1), 427–431.

Du X., Yu C.L., & Hayes D.J. (2011). Speculation and volatility spill-over in the crude oil and agricultural commodity markets: A Bayesian analysis. *Energy Economics*, 33, 497–503.

Enders W. (1995). *Applied econometric time series*. New York: USA, John Wiley & Sons, Inc.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica, 50*, 987–1007.

Engle, R.F., & Granger, C.W.J. (1987). Co-integration and error correction: representation, estimation, and testing. *Econometrica*, *55*, 251–276.

Engle, R.F., & Kroner, F. (1995). Multivariate simultaneous Generalized ARCH. *Econometric Theory*, *11*(1), 122–150.

Engle, R.F., & Yoo, B. (1991). Forcasting and testing in cointegration systems. *Journal of Econometrics*, *35*(1): 143 – 159.

Frank J., & Garcia P. (2010). How strong are the linkages among agricultural, oil, and exchange rate markets? In: *Applied commodity price analysis, forecasting, and market risk management*. Proceedings of the NCCC-134 Conference, St. Louis, MO.

Fuller, W. A. (1976). *Introduction to statistical time series*. New York: USA, John Wiley & Sons.

Gilbert, C.L. (2010). How to understand high food prices. *Journal of Agricultural Economics*, *61*(1), 398–425.

Goodwin, B.K. and Piggott, N.E. (2001). Spatial market integration in the presence of threshold effects. *American Journal Agricultural Economics*, 83, 302–317.

Gozgor G., & Kablamaci B. (2014). The linkage between oil and agricultural commodity prices in the light of the perceived global risk. *Agricultural Economics*, *60*(1), 332–342.

Granger, C.W.J. (1969). Investigating Causal Relations by Econometric Models and Cross-spectral Methods. *Econometrica*, 37, 424–438.

Hannan, E. J. (1970). *Multiple Time Series*. New York: USA, John Wiley & Sons.

Harri, A., Nalley, L., & Hudson D. (2009). The relationship between oil, exchange rates, and commodity prices. *Journal of Agricultural and Applied Economics*, *41*(1), 501–510.

Johansen S., & Juselius K. (1990). Maximum likelihood estimation and inferences on co-integration with application to the demand for money. *Oxford Bulletin of Economics and Statistics*, *52*(1): 169–210.

Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control*, *12*(2): 231–254.

Johansen, S. (1991). Estimation and hypothesis testing of cointegrating vectors in gaussian vector autoregressive models. *Econometrica 59*, 1551–1580.

Kalkuhl, M., Kornher, L., Kozicka, M., Boulanger, P., & Torero, M. (2013). *Conceptual framework on price volatility and its impact on food and nutrition security in the short term* (Paper 15). Food Secure Working. The Hague: LEI Wageningen UR.

Kroner, K.F., & Ng, V.K. (1998). Modelling asymmetric co-movements of asset returns. *Revised Financial Studies*, 11, 817–844.

Kwon D., & Koo W.W. (2009). Price transmission channels of energy and exchange rate on food sector: A disaggregated approach based on stage of process. Agricultural & Applied Economics Association 2009 AAEA & ACCI Joint Annual Meeting, Milwaukee, Wisconsin, July 26–29, 2009.

Mackinnon J.G., Haug A.A., & Michelis L. (1999). Numerical distribution functions of likelihood ratio tests for cointegration. *Journal of Applied Econometrics*, *14*, 563–577.

Mutuc, M., Pan S., & Hudson D. (2010). What drives commodity prices more: oil demand or supply shocks? Agricultural & Applied Economics Association 2010 AAEA & CAES Joint Annual Meeting, Denver, Colorado, July 25–27, 2010.

Naka, A., & Tufte, D. (1997). Examining impulse response functions in cointegrated system. *Application of Econometrics*, *29*(1), 1593–1603.

Nazlioglu S. (2011). World oil and agricultural commodity prices: Evidence from nonlinear causality. *Energy Policy*, *39*(3), 2935–2943.

Nazlioglu S., & Soytas S. (2012). Oil price, agricultural commodity prices, and the dollar: A panel cointegration and causality analysis. *Energy Economics*, *34*(2), 1098–1104.

Nazlioglu S., Erdem C., & Soytas S. (2013). Volatility spill-over between oil and agricultural commodity markets. *Energy Economics*, *36*(2), 658–665.

Nelson, D.B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica*. *59*, 347–370.

Ng, S., & Perron, P. (2001). Lag length section and the construction of unit root test with good size and power. *Econometrica*, *69*, 1519-54.

Obstfeld, M., and Taylor, A. (1997). Nonlinear Aspects of Goods-Market Arbitrage and Adjustment: Heckscher's Commodity Points Revisited. *Journal of Japanese International Economics*, 11, 441–479.

Phillips, P. C. B. (1991). Optimal inference in cointegrated systems. *Econometrica*, *59*, 238-306.

Saghaian S.H. (2010). The impact of the oil sector on commodity prices: correlation or causation? *Journal of Agricultural and Applied Economics*, *42*(1): 477–485.

Sarker, R., & Jaramillo-Villanueva. J. L. (2007). Exchange rate sensitivity of Mexican maize imports from the united states. The American Agricultural Economics Association Annual Meeting in Portland, Oregon, July 29-August 1.

Serra, T. (2014). Price volatility in Niger millet markets. *American Journal of Agricultural Economics, 80*(1), 35-67.

Serra, T., & Gil, J.M. (2012). Price volatility in food markets: can stock building mitigate price fluctuations? *Energy Economics*, *36*(1), 124-130.

Serra, T., Zilberman, D., Gil, J.M., & Goodwin, B.K. (2011). Nonlinearities in the U.S. Corn–ethanol–oil–gasoline price system. *European Review of Agricultural Economics*, *38*(4), 35–45.

Sims, C. A., Stock J. H. & Watson M. W. (1990). Inference in linear time series models with some unit roots. *Econometrica, 58*, 113-144.

Solo, V. (1984). The order of differencing in ARIMA Models. *Journal of the American Statistical Association*. *79*(1), 916-921.

Stock, J.H. (1987). Asymptotic properties of least squares estimators of cointegrating vectors, *Econometrica*, *55*: 1035–1056.

Stock, J.H, & Watson, M. W. (1996). Evidence on structural instability in macroeconomic time series relations. *Journal of Business and Economic Statistics 14*(1), 11–30.

Tadese, G., Algieri, B., Kalkuhl, M. & Von Braun, J. (2014): drivers and triggers of international food price hikes and volatility. *Food Policy*, *47*(4), 117-128.

Toda, H.Y., & Yamamoto, T. (1995). Statistical inference in Vector Autoregression with possibly integrated processes. *Journal of Econometrics*, *66*(1): 225–250.

Trostle, R. (2008). Global agricultural supply and demand factors contributing to the recent increase in food commodity prices. *Agricultural Economics*, *36*(2), 216–391.

Trujillo-Barrera, A., Mallory, M., & Garcia, P. (2012). Volatility spill-overs in U.S. Crude oil, ethanol, and corn futures markets. *Journal of Agricultural and Resource Economics*, 37(1), 247–262.

Wang Y., Wu C., and Yang L. (2014). Oil Price Shocks and Agricultural Commodity Prices. *Energy Economics*, 44, 22–35.

Wixson, S., & Katchova, A.L. (2012). Price asymmetric relationships in commodity and energy markets. Working Paper University of Kentucky

Zhang, Z., Lohr, L., Escalante, C., and Wetzstein, M. (2009). Ethanol, corn, and soybean price relations in a volatile vehicle-fuels market. *Energies*, *2*(1), 320–339

APPENDICES

APPENDIX A: Test for the difference in mean of FP

Pre–food crisis period against First crisis period	First crisis period against Post First crisis period	Post First crisis period against Second crisis period	Second crisis period against Post second crisis period
-0.88 (0.2412) [0.0000]	0.77 (0.0183) [0.0000]	-1.09 (0.1128) [0.0000]	0.78 (0.1841) [0.0000]

(Standard errors in bracket, p-values in parentheses)

APPENDIX B: Results of Unit Root Tests

Results of unit root tests for the pre-crisis period

	ADF Test		Philip-Perron Test	
Series	**Level**	**First Difference**	**Level**	**First Difference**
FP	0.8553	0.0000	0.8605	0.0000
PP	0.7587	0.0000	0.7600	0.0000
RER	0.3625	0.0001	0.2616	0.0001
RIR	0.3820	0.0000	0.4334	0.0000

Results of unit root tests for the first crisis period

	ADF Test		Philip-Perron Test	
Series	**Level**	**First Difference**	**Level**	**First Difference**
FP	0.561	0.000	0.787	0.000
PP	0.676	0.000	0.681	0.000
RER	1.000	0.000	1.000	0.000
RIR	0.032	0.000	0.896	0.000

Results of unit root tests for the post first crisis period

	ADF Test		Philip-Perron Test	
Series	**Level**	**First Difference**	**Level**	**First Difference**
FP	0.1842	0.009	0.417	0.012
PP	0.433	0.031	0.502	0.038
RER	0.051	0.009	0.051	0.008
RIR	0.502	0.006	0.469	0.006

Results of unit root tests for the second crisis period

	ADF Test		Philip-Perron Test	
Series	**Level**	**First Difference**	**Level**	**First Difference**
FP	0.039	0.000	0.537	0.000
PP	0.4830	0.000	0.494	0.000
RER	0.647	0.000	0.723	0.000
RIR	0.586	0.000	0.591	0.000

Results of unit root tests for the post second crisis period

	ADF Test		Philip-Perron Test	
Series	**Level**	**First Difference**	**Level**	**First Difference**
FP	0.882	0.000	0.859	0.000
PP	0.817	0.000	0.814	0.000
RER	0.767	0.001	0.780	0.000

RIR	0.391	0.000	0.486	0.000

APPENDIX C: Unrestricted Cointegration Rank Tests

Results of Unrestricted cointegration rank tests for the pre-crisis period

Trace Test			Maximum Eigenvalue Test		
Hypothesized No. of CE(s)	Trace Statistic	p-value*	Hypothesized No. of CE(s)	Max-Eigen Statistic	p-value*
None ***	58.666	0.004	None **	27.856	0.046
At most 1 **	30.810	0.038	At most 1	17.021	0.171
At most 2	13.789	0.089	At most 2	8.673	0.314
At most 3	3.116	0.324	At most 3	3.116	0.324

Results of Unrestricted cointegration rank tests for the first crisis period

Trace Test			Maximum Eigenvalue Test		
Hypothesized No. of CE(s)	Trace Statistic	p-value*	Hypothesized No. of CE(s)	Max-Eigen Statistic	p-value*
None ***	70.857	0.000	None ***	51.733	0.000
At most 1	19.123	0.484	At most 1	10.680	0.679
At most 2	8.443	0.419	At most 2	7.569	0.424
At most 3	0.874	0.350	At most 3	0.874	0.350

Results of Unrestricted cointegration rank tests for the post first crisis period

Trace Test			Maximum Eigenvalue Test		
Hypothesized No. of CE(s)	Trace Statistic	p-value*	Hypothesized No. of CE(s)	Max-Eigen Statistic	p-value*

None ***	51.049	0.003	None **	24.195	0.050
At most 1 **	26.854	0.023	At most 1 **	17.990	0.047
At most 2	8.864	0.177	At most 2	8.104	0.168
At most 3	0.760	0.441	At most 3	0.760	0.441

Results of Unrestricted cointegration rank tests for the second crisis period

Trace Test			Maximum Eigenvalue Test		
Hypothesized No. of CE(s)	Trace Statistic	p-value*	Hypothesized No. of CE(s)	Max-Eigen Statistic	p-value*
None ***	79.937	0.000	None ***	40.085	0.001
At most 1 ***	39.852	0.003	At most 1 ***	29.640	0.003
At most 2	10.212	0.265	At most 2	6.921	0.499
At most 3	3.291	0.370	At most 3	3.291	0.370

Results of Unrestricted cointegration rank tests for the post second crisis period

Trace Test			Maximum Eigenvalue Test		
Hypothesized No. of CE(s)	Trace Statistic	p-value*	Hypothesized No. of CE(s)	Max-Eigen Statistic	p-value*
None ***	61.960	0.001	None ***	37.563	0.002
At most 1	24.396	0.184	At most 1	14.997	0.289
At most 2	9.398	0.330	At most 2	7.465	0.436
At most 3	1.933	0.164	At most 3	1.933	0.164

*Note : *** and ** denotes rejection of the hypothesis at the 1%, and 5% levels respectively*
**MacKinnon-Haug-Michelis (1999) p*-values

APPENDIX D: Vector Error Correction Model Estimates

Vector error correction model estimates for the pre–crisis period

$$D(FP) = \lambda\,(FP_{(-1)} - 0.94PP_{(-1)} - 0.82RER_{(-1)} - 0.08RIR_{(-1)})$$

Variable	Coefficient	Std. Error	t-Statistic	p-value
λ	-0.1021***	0.0228	-4.4762	0.0000
D(FP(-1))	-0.1135	0.0963	-1.1781	0.2400
D(FP(-2))	-0.2314**	0.0968	-2.3908	0.0286
D(PP(-1))	0.2719***	0.0652	4.1697	0.0000
D(PP(-2))	0.3239***	0.0680	4.7637	0.0000
D(RER(-1))	1.0999***	0.2535	4.3390	0.0000
D(RER(-2))	1.0061***	0.2451	4.1048	0.0000
D(RIR(-1))	0.0542***	0.0120	4.5133	0.0000
D(RIR(-2))	0.0867***	0.0213	4.0690	0.0000
ε	0.0182**	0.0077	2.3674	0.0199
R-squared	0.6701		Prob(F-statistic)	0.0000
Adj. R-squared	0.5460		DW stat	2.0203
F-statistic	6.6218			

Vector error correction model estimates for the first crisis period

$D(FP) = \lambda *(FP_{(-1)} - 1.93*PP_{(-1)} - 2.12*RER_{(-1)} - 1.10*RIR_{(-1)})$

Variable	Coefficient	Std. Error	t-Statistic	p-value
λ	-0.2525***	0.0460	-5.4886	0.0000
D(FP(-1))	-0.7962***	0.1989	-4.0032	0.0037
D(PP(-1))	0.7320**	0.3131	2.3378	0.0360
D(RER(-1))	1.2439***	0.2744	4.5333	0.0000
D(RIR(-1))	0.4534***	0.0946	4.7927	0.0000
ε	0.1062**	0.0472	2.2506	0.0454
R-squared	0.8344		Prob(F-statistic)	0.0000
Adj. R-squared	0.7707		D-W stat	2.0015
F-statistic	13.1053			

Vector error correction model estimates for the post first crisis period

$D(FP) = \lambda *(FP_{(-1)} - 0.85*PP_{(-1)} - 3.22 *RER_{(-1)} - 0.09*RIR_{(-1)})$

Variable	Coefficient	Std. Error	t-Statistic	p-value
λ	-0.1483***	0.0300	-4.9437	0.0000
D(FP(-1))	0.5629**	0.1939	2.9035	0.0116
*D(PP(-1))	0.1911***	0.0399	4.7896	0.0000

D(RER$_{(-1)}$)	1.9331***	0.3947	4.8976	0.0000
D(RIR$_{(-1)}$)	0.0131***	0.0025	5.2529	0.0000
ε	0.0182***	0.0037	4.9280	0.0000
R-squared	0.6144		Prob(F-statistic)	0.0009
Adj. R-squared	0.4767		D-W stat	2.0329
F-statistic	7.4623			

Vector error correction model estimates for the second crisis period

D(FP) = λ *(FP$_{(-1)}$ - 1.42*PP$_{(-1)}$ - 4.38*RER$_{(-1)}$ - 1.10*RIR$_{(-1)}$)

Variable	Coefficient	Std. Error	t-Statistic	p-value
λ	-0.8849***	0.1569	-5.6400	0.0000
D(FP$_{(-1)}$)	0.8370***	0.2089	4.0063	0.0039
D(PP$_{(-1)}$)	0.8296***	0.1619	5.1244	0.0000
D(RER$_{(-1)}$)	1.2330***	0.2412	5.1121	0.0000
D(RIR$_{(-1)}$)	0.4385***	0.0969	4.5252	0.0000
ε	0.0123***	0.0031	3.9782	0.0066
R-squared	0.7413		Prob(F-statistic)	0.0023
Adj. R-squared	0.5474		D-W stat	2.0435
F-statistic	4.8224			

Vector error correction model estimates for the post second crisis period

D(FP) = λ *(FP$_{(-1)}$ - 1.10*PP$_{(-1)}$ - 1.06*RER$_{(-1)}$ - 0.01*RIR$_{(-1)}$)

Variable	Coefficient	Std. Error	t-Statistic	p-value
λ	-0.1454**	0.0582	-2.4968	0.0156
D(FP$_{(-1)}$)	0.2127	0.1356	1.5687	0.1224
D(FP$_{(-2)}$)	-0.5828***	0.1394	-4.1806	0.0000
D(PP$_{(-1)}$)	0.2363***	0.0589	4.0112	0.0009
D(PP$_{(-2)}$)	0.2348***	0.0563	4.1700	0.0000
D(RER$_{(-1)}$)	0.2953***	0.0730	4.0458	0.0007
D(RER$_{(-2)}$)	0.2910***	0.0726	4.0085	0.0022
D(RIR$_{(-1)}$)	0.0504***	0.0120	4.2023	0.0000
D(RIR$_{(-2)}$)	0.0521***	0.0122	4.2740	0.0000
ε	0.0133***	0.0032	4.1551	0.0000

R-squared	0.7288	Prob(F-statistic)	0.0000
Adj. R-squared	0.6025	Durbin-Watson	
F-statistic	7.8127	stat	2.0282

Source: Author's estimate

Note: FP is the log of Food Price Index, PP is the log of petroleum price, RER is the log of real exchange rate, and RIR is the log of real interest rate, λ is the speed of adjustment, ε is the error term

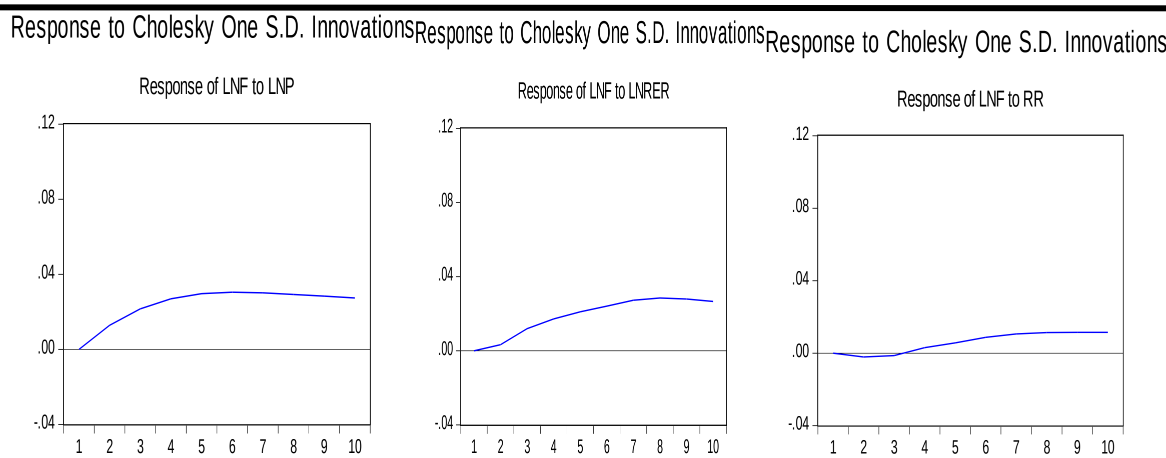
**** and ** denotes significance at the 1%, and 5% levels respectively*

APPENDIX E: Chow Test for Structural Breaks

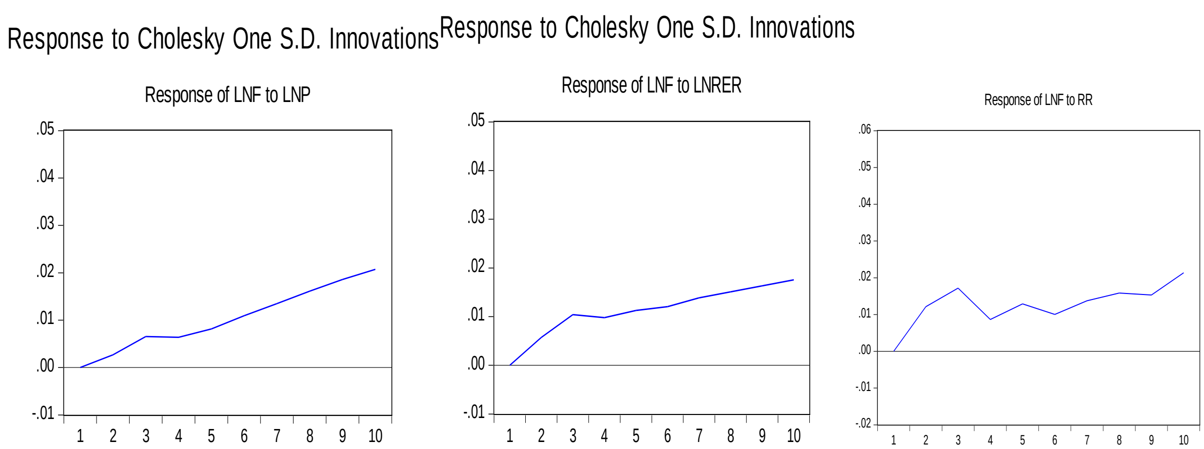
F-statistic	Prob.F(52,180)	Wald Statistic	Prob. Chi-Square(52)
8.8328	**0.0000**	**459.3079**	**0.0000**

APPENDIX F: Impulse response functions for food price

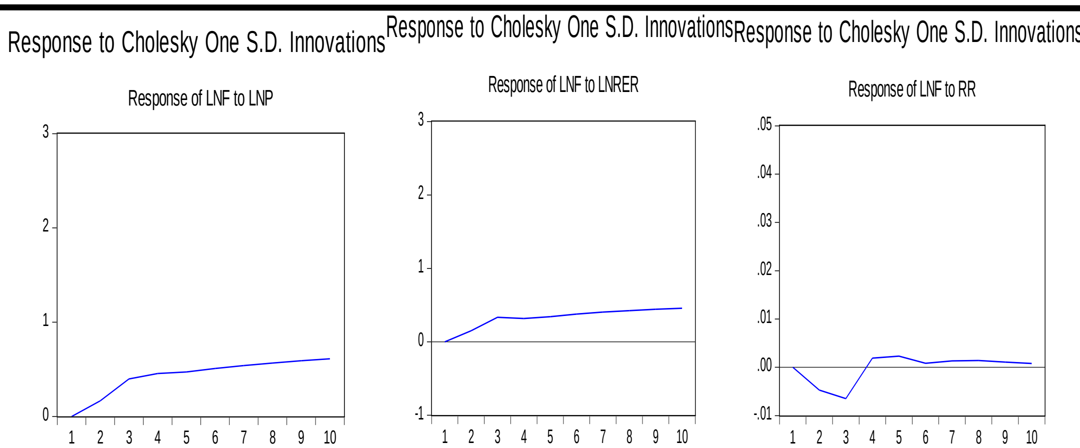
Impulse response functions for food price in the pre-crisis-period



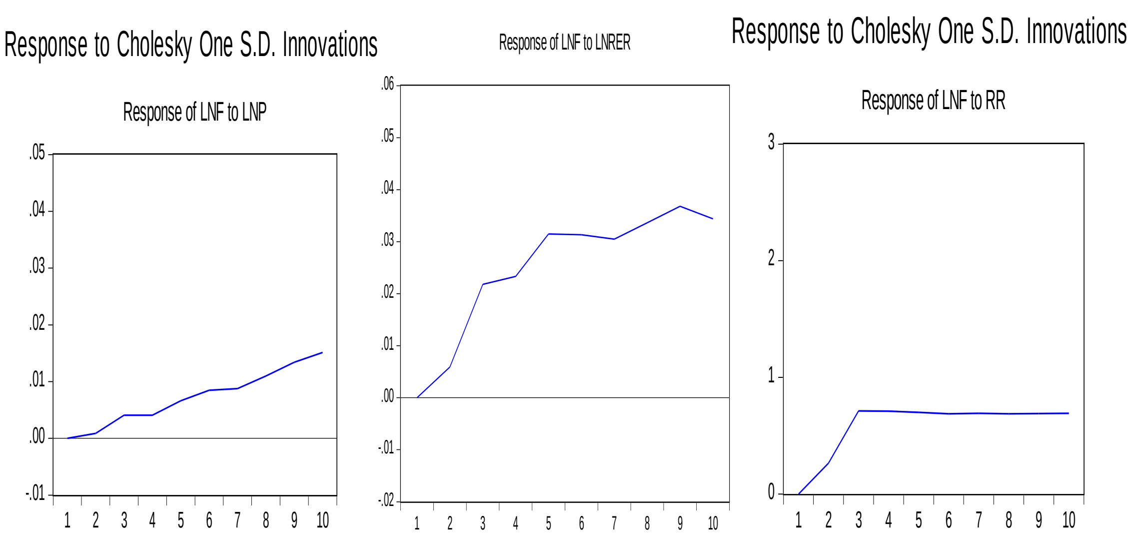
Impulse response functions for food price in the first crisis period



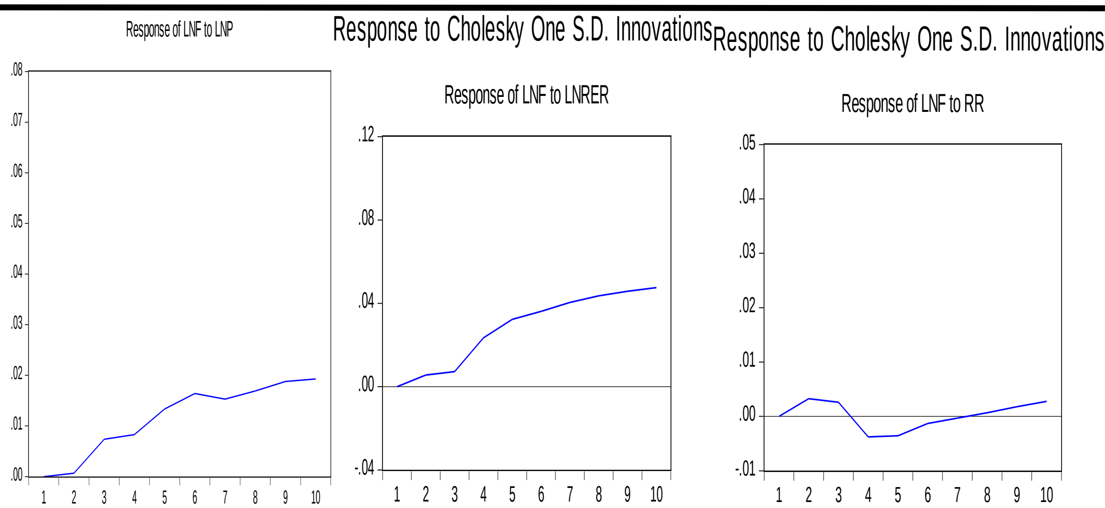
Impulse response functions for food price in the post first crisis period



Impulse response functions for food price in the second crisis period



Impulse response functions for food price in the post second crisis period


Response of LNF to LNP
Response to Cholesky One S.D. Innovations
Response of LNF to LNRER
Response to Cholesky One S.D. Innovations
Response of LNF to RR
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