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Abstracts

This paper investigates volatility spillover across crude oil market and wheat and corn markets. The corn commodity is taken here to assess the impact of change in demand for biofuel on wheat market. Results of multivariate GARCH model show evidence of corn price volatility transmission to wheat market . Our results indicate that while shocks (unexpected news) in crude oil market have significant impact on volatility in wheat and corn markets, the effect of crude oil price changes on corn and wheat markets is insignificant. The impulse response analysis indicate shocks in oil markets have permanent effect on food commodity price changes. Also indicated that fertilizers markets influenced by own-shocks and shocks in oil markets.

Keywords: Volatility, global food, impulse response
JEL Classification: C53, C54, Q17, Q18

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1-Introduction:

The sharp increase in global food commodity prices in recent years have raised concerns to governments in developing countries as increasing number of low income groups became vulnerable to high inflation rates. Increasing volatility in agriculture commodity prices creates uncertainty to farmers to meet the rising demand for agricultural food commodities, and to consumers to manage future spending plans.

Analysts attribute the rising volatility in food commodity prices to a number of factors, among them speculations in future commodity markets (FAO, 2008); crude oil price changes and its impact on bio-fuel commodity markets (Institute for Agriculture and Trade Policy, 2008); and to structural change in global demand for food items, caused by the rapid economic growth in countries like China and India (Jeffrey Frankel, 2008a). While substantial research efforts have been taking place for the past few years on food policy issues, the issue of energy markets volatility transmission to global food markets have received relatively little attention in empirical research[1]. It is widely believed that global food system is heavily dependent on energy prices, not only through transportation cost effect, but also energy as inputs in food production and packaging processes. It is also viewed that oil price hikes can influence food prices by shifting

[1] With exception of the research papers by Du et al., 2009; Onour,2010;Onour and Sergi 2011..

production from wheat and rice to produce corn and sugar cane for biofuel production. Another factor that may also exert an influence on global food price hikes is the increasing demand for food commodities by the fast growing economies, such as China, India, and Brazil. Whatever would be the prime cause behind the soaring food commodity prices, it is important to point out that investigation of volatility transmission between oil price and food prices can help capturing empirical regularities that characterize commodity markets. While the literature on volatility of food commodity markets in general is scarce, compared to the literature on financial asset markets, a number of authors (Onour and Sergi 2011; Du et al.2009) investigated spillover effect of crude oil price on global food prices in bivariate analysis framework. However, it is clear that more robust analysis of volatility in food prices can be captured through multivariate approach that takes into account interdependence between food commodity markets.

This paper is motivated by the growing literature on multivariate GARCH models that characterize the pattern of information flows among asset markets.

The reminder of the paper is structured as follows. Section two highlight volatility transmission of crude oil prices to global food commodity markets; Section three presents the methodology of the research; Section four includes descriptive statistic of the sample data used in the estimation process. Section five discusses the empirical results. The final section concludes the study.

2- Volatility in global food prices:

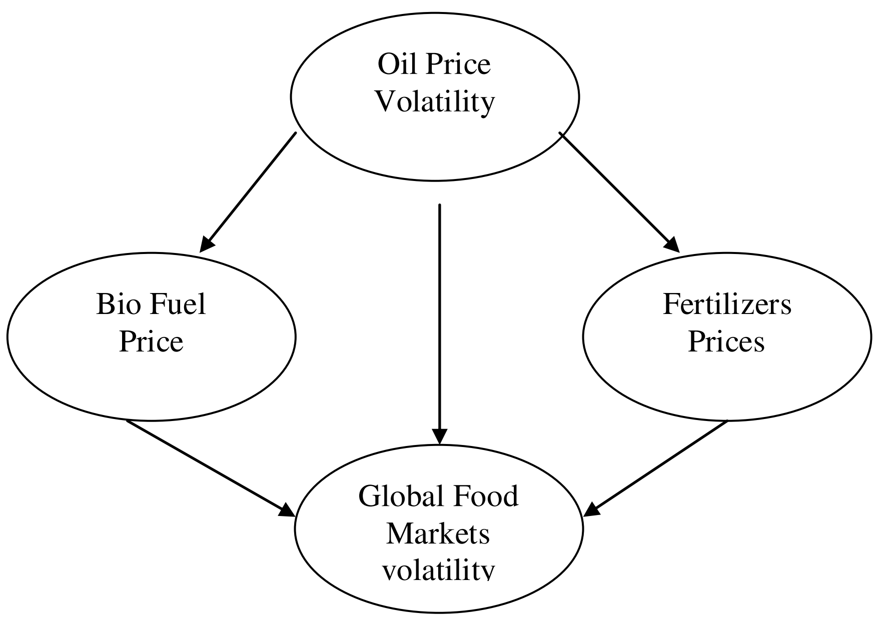
The soaring global food prices can best be understood in terms of structural and cyclical factors[2]. Unpredictability of future food prices can create problems to poor households as they become more constrained to adjust their food spending budget to rising prices, and producers fail to respond in time to the rising prices due to the seasonal time-cycle of agricultural production. Furthermore, disruptive nature of supply of food production and globally increasing demand for food commodities makes global food market thin[3]. Also among factors contributed towards high food prices in recent years is export ban policies adopted by a number of wheat and rice producing countries as a result of recent environmental calamities in North America , Australia, and Russia. Export bans by major food commodity exporters exacerbated price volatility as speculations in future commodity markets fueled already volatile food commodity markets. It is strongly believed that the effects of high oil prices also aggravated already volatile and unstable food prices. The transmission effect of oil prices on global food prices, indicated in figure (1), show that oil price effects can transmit to global food prices through multiple of routes. Oil price rise can transmit to food markets directly, in a form of shipment and transportation costs rise, or indirectly by increasing demand for cereals (corn and sugar cane)

[2] Structural factors are long-term factors that can cause a permanent shifts in demand or supply, whereas cyclical factors are due to short-term temporary supply and demand shifts. Structural and cyclical forces create a system more sensitive to supply shocks and less predictable.

[3] Thinness of markets imply only small proportion of total world production is traded in world markets. According to FAO (2008e) report, only 18 percent of world wheat production and 6 percent of world rice production is exported; the rest is either consumed or stocked in a few production sources.

for biofuel production purposes, and also by raising the cost of fertilizers.Other factors, such as monetary policies, and currency fluctuations may also contribute to global food price volatility. Low interest rates reduce the price of storage and encourage storage of real commodities (Jeffrey Frank, 2008b). Also the depreciation of the US dollar against other major convertible currencies can raise demand for commodities as commodities priced in dollar terms become relatively cheaper. Also there is a strong belief that speculations in future commodity markets are a major a factor behind soaring food commodity prices[4].

Fig.(1):Crude oil price transmission effects



[4] After the U.S deregulation Act of 2000, that officially ensured the deregulation of food commodity markets, for the first time it has been permitted in U.S to trade in food commodities future contracts. As a result, when a farmer sign a contract to sell his future crop to a grain trader at pre-specified price, the trader on his side can sell the future contract to another speculator (e.g hedge or pension fund) at a higher price. Since the size of these future speculative contracts is huge in size (quantity and value) the prices in speculative contracts can set any new future contracts and influence spot market prices as well.

3-Methodology

3.1: Volatility transmission

To capture volatility in energy and food markets consider the following mean return equation:

$$R_{it} = \mu_i + e_{it} \qquad (1)$$

$$where, \quad e_{t/t-1} \sim N(0, h_t)$$

$$and,$$

$$h_t = \beta_0 + \sum_{i=0}^{q} \beta_i e^2{}_{t-i} + \sum_{i=1}^{p} \alpha_i h_{t-i} \qquad (2)$$

Where R_{it} is the return on price index i between time t-1 and t, μ_i is a long term drift coefficient, and e_{it} is the error term for the return on index i, at time t, with mean zero and conditional variance of h_t.

Conditional volatility in equation (2), depicted as GARCH process. To account for cross correlation effects of volatility we can adopt multivariate GARCH model, which is known as VECH model introduced by Bollerslev, Engle, and Wooldridge (1988), stated as:

$$Vech(H_t) = B_0 + \sum_{i=1}^{p} B_i vech(H_{t-i}) + \sum_{i=0}^{q} A_i vech(e_{t-i} e'_{t-i})$$

The notation vech(.) is the vector half operator which transforms asymmetric (dxd) matrix into a vector of length d=(d+1)d/2 by stacking the elements of the upper triangular half of the matrix, and H_t denotes the conditional variance matrix. One major problem related to vech specification of multivariate GARCH models is the large number of parameters included in the estimation process.

An alternative approach proposed by Engle and Kroner (1995) , known as the Baba, Engle, Kraft and Kroner or BEKK representation specify the conditional variance in GARCH (p,q) as:

$$H_t = \alpha\alpha' + \sum_{k=1}^{K} \sum_{i=1}^{p} \beta'_{ki} H_{t-i} \beta_{ki} + \sum_{k=1}^{K} \sum_{i=1}^{q} A'_{ki} e_{t-i} e'_{t-i} A_{ki} \qquad (3)$$

where the individual components of α , B and A, matrices in our four commodity case are as follows:

$$\alpha = \begin{bmatrix} \alpha_{11} & 0 & 0 & 0 \\ \alpha_{21} & \alpha_{22} & 0 & 0 \\ \alpha_{31} & \alpha_{32} & \alpha_{33} & 0 \\ \alpha_{31} & \alpha_{32} & \alpha_{33} & \alpha_{34} \end{bmatrix} \quad B = \begin{bmatrix} b_{11} & b_{12} & b_{13} & b_{14} \\ b_{21} & b_{22} & b_{23} & b_{24} \\ b_{31} & b_{32} & b_{33} & b_{34} \\ b_{41} & b_{42} & b_{43} & b_{44} \end{bmatrix} \quad A = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \\ a_{31} & a_{32} & a_{33} & a_{34} \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix}$$

The matrix B reflects the extent to which current levels of conditional variances are related to past conditional variances. Parameters in matrix A estimates the extent to which conditional variances are linked with past squared errors. The elements in A captures the impact of news on conditional volatility.

The coefficients in the variance terms in equation (3) reflect direct volatility transmission, and the coefficients of covariance terms represent indirect volatility transmission, whereas squared residuals coefficients reflect transmission of news among commodity markets. Estimation of parameters in (3) performed maximizing the log-likelihood function:

$$L(\Omega) = -N \ln(2\pi) - (1/2) \sum_{t=1}^{N} (1\ln|H_t| + e'_t H_t^{-1} e_t) \qquad (4)$$

where N is the number of observations and Ω represents the parameter vector to be estimated[5].

3.2: Impulse response

[5] Maximization of the log likelihood in (4) has QMLE features.

To assess persistence of oil price effects on global food prices in this section we show how impulse response function can be utilized. Letting x_t *and* y_t are properly transformed, input and output series so that both are stationary, the output series y_t and the input series x_t are related through the linear filter,

$$y_t = v(B)x_t + \eta_t \qquad (5)$$

where $v(B) = \sum_{j=-\infty}^{j=\infty} v_j B^j$ is referred to as the transfer function filter (Wei 1990), and η_t is the noise series of the system, that is independent of the input series x_t. The coefficients, v_j, in the transfer function model (5) are called the impulse response weights. As a function of j, v_j is also called the impulse response function. The transfer function model is said to be stable if the sequence of impulse response weights is absolutely summable , or $\sum |v_j| < \infty$, which implies that the response of output series to a shock in the input variable dies down to its pre-shock level as time passes on. In the case of unstable system a shock to the input series leave a permanent effect on the output series. To construct impulse response weights from the transfer function noise model (5) we adopted the following procedures. Assuming that the input series x_t, follows an ARMA process: $\Phi_x(B)x_t = \Theta_x(B)e_t$, where

$$\Phi_r(B) = \Phi_0 - \Phi_1 B - \Phi_2 B^2 - ..... - \Phi_r B^r$$
$$\Theta_s(B) = 1 - \Theta_1 B - \Theta_2 B^2 - .... - \Theta_s B^s$$

for B^s is a lag operator of order s, and e_t is white noise. The series e_t, is often called the prewhitened input series, so that $e_t = \frac{\Phi_x(B)}{\Theta_x(B)} x_t$.

Applying the same prewhitened transformation to the output series y_t, we obtain a filtered output series, $u_t = \frac{\Phi_x(B)}{\Theta_x(B)} y_t$. Then the transfer function model becomes:

$$u_t = v(B)e_t + \varepsilon_t \qquad (6)$$

$$where \ \varepsilon_t = \Theta_x^{-1}(B)\Phi_x(B)\eta_t$$

The impulse response weights, v_j in (6) can therefore be found as $v_k = \frac{\sigma_\beta}{\sigma_e}\rho_{e\beta}(k)$, where $\sigma_\beta \ and \ \sigma_e$ are respectively volatility measures of prewhitened output and input series, and $\rho_{\beta e}$ is the cross correlation function. When the elements of v_k treated as a function k, traces out the expected response of the output to a unit shock. When the effect of impulse weights vanish over time , the effect of a shock on output is transitory. However, if the effect of the impulse response do not converge to zero the impact of the shock is permanent . As a result, if the effect of oil shock on food commodity markets is transitory the impact is expected to die out within a short period of time, however, if it is permanent the impact of the shock is expected to converge to a limit that is significantly different from zero.

4-Data Analysis:

Data employed in this study includes monthly data on crude oil prices (Dubai Fateh); a composite index for fertilizers[6]; and the prices

[6] The fertilizers include TSP(triple Superphosphate), Urea(Black sea),DAP(diammonium phosphate), and Potassium chloride (muriate of potash).

of wheat and corn, during the sample period from January 1992 to February 2011.

Results in table (2) indicate corn prices exhibit relatively higher average return , and higher unconditional volatility compared to wheat. The skewness and kurtosis coefficients reveal all prices (except crude oil) exhibit peakness and fat tailedness relative to a normal distribution. The high values of kurtosis statistics indicate price distribution is characterized by high peakness (fat tailedness) . The positive skewness results indicate a higher probability for stock prices increase. The sample autocorrelation statistic indicated by Ljung-Box, Q (10) statistic, reject the null hypothesis of uncorrelated price for ten lags for all commodity markets. The high values for $Q^2(10)$ test statistic suggest conditional homoskedasticity can be rejected in favor of serial interdependence of conditional volatility series. Phillips-Perron unit root test reject stationarity condition at the first difference of all prices.

Table (2): Descriptive Statistics

	Wheat	Corn	Oil	Fertilizers
Mean	0.025	1.27	0.43	1.50
St.deviation:	0.34	12.07	4.10	23.9
Skewness:	1.49	1.34	0.90	1.26
Kurtosis:	2.68	1.74	0.42	1.95

Q(10)	876*	865*	419*	747*
(p-value)	(0.00)	(0.00)	(0.00)	(0.00)
$Q^2(10)$	704*	713*	369*	562*
(p-value)	(0.00)	(0.00)	(0.00)	(0.00)
PP unit root:				
-Level	1.86	10.3*	2.68	3.1
-First diff	43.7*	83.5*	24.0*	82.7*

*Significant at 5 per cent significance level.

Results of the sample autocorrelation function (ACF) and partial autocorrelation function (PACF), in table (2) show the stationary input series can be modeled as AR(2). Accordingly, in the light of the ACF and PACF results, the fitted model is $(1+0.08B-0.95B^2)x_t = e_t$ and the fitted output series is

$$(1+0.08B-0.95B^2)y_t = u_t$$

Table (2): ACF and PACF

lags	1	2	3	4	5	6	7	8	9	10
ACF S.E	-0.08 0.07	0.95 0.07	-0.10 0.07	0.89 0.07	-0.11 0.07	0.83 0.07	-0.12 0.07	0.80 0.07	-0.11 0.07	0.72 0.07
PACF S.E	-0.08 0.07	0.95 0.07	-0.19 0.07	-0.14 0.07	0.05 0.07	0.06 0.07	0.10 0.07	0.13 0.07	-0.01 0.07	-.05 0.07

*S.E stand for standard errors.

5. Results

Results of multivariate GARCH model (equations (1-3)) reported in table (2), show evidence of corn price volatility transmission to wheat price, implying significant impact of changes in demand for biofuel on wheat price volatility. Also indicated that while shocks (unexpected news) in crude oil market have significant impact on volatility in wheat and corn markets, the effect of crude oil price changes on corn and wheat prices changes is insignificant. There is also evidence that volatility in food prices is influenced by volatility in fertilizers markets. However, volatility in fertilizers markets is affected indirectly by volatility in food prices and energy prices, as both covariance terms $(h_{12,t} \text{ and } h_{13,t})$ are significant and positive. Fertilizers markets are also affected by own-shocks and shocks in energy markets, as both $(e^2{}_{1t} \text{ and } e^2{}_{3t})$ significant and positive. As expected, there is no evidence of volatility transmission from food commodity markets (wheat and corn) to crude oil market. This may reveal the influence of speculation in crude oil markets on global food price volatility.

The impulse response analysis indicate shocks in oil markets have permanent effect on food commodity price changes. Also indicated that fertilizers markets influenced by own-shocks and shocks in oil markets. This evidence support the view that political stability in Middle East oil producing countries may play a significant role in global food price stabilization.

Table (3): Volatility transmission

Independent Variables	Fertilizers ($h_{11,t+1}$)	Wheat ($h_{22,t+1}$)	oil ($h_{33,t+1}$)	Corn $h_{44,t+1}$
$h_{11,t}$ p-value	-0.07 (0.25)	0.36* (0.00)	-0.03 (0.65)	0.05 (0.30)
$h_{12,t}$ p-value	-0.01 (0.41)	-0.03* (0.01)	-0.006 (0.68)	0.032* (0.00)
$h_{13,t}$ p-value	-0.01 (0.91)	0.05 (0.67)	0.055 (0.68)	-0.02 (0.84)
$h_{14,t}$ p-value	-0.01 (0.70)	0.01 (0.56)	0.008 (0.79)	0.004 (0.85)
$h_{22,t}$ p-value	0.77 (0.36)	-0.07 (0.42)	-0.03 (0.73)	0.18* (0.00)
$h_{23,t}$ p-value	-0.04 (0.54)	-0.06 (0.36)	-0.004 (0.95)	0.03 (0.49)
$h_{24,t}$ p-value	0.002* (0.02)	-0.001 (0.64)	-0.001 (0.25)	0.00 (0.98)
$h_{33,t}$ p-value	-0.16* (0.03)	-0.04 (0.62)	-0.03 (0.68)	-0.01 (0.79)
$h_{34,t}$ p-value	-0.008* (0.00)	-0.0001 (0.98)	0.005 (0.10)	-0.002 (0.38)
$h_{44,t}$ p-value	0.12 (0.22)	0.15 (0.14)	-0.16 (0.14)	-0.10 (0.16)
$e_{1,t}{}^2$ p-value	-0.0001 (0.71)	0.0002 (0.27)	-0.0001 (0.52)	-0.0001 (0.39)
$e_{1t}e_{2t}$ p-value	0.01 (0.39)	0.03* (0.01)	0.007 (0.64)	-0.031* (0.01)
$e_{1t}e_{3t}$ p-value	0.02 (0.89)	-0.04 (0.70)	-0.05 (0.68)	0.021 (0.82)
$e_{1t}e_{4t}$ p-value	0.01 (0.72)	-0.02 (0.45)	-0.008 (0.79)	-0.003 (0.90)
$e_{2,t}{}^2$ p-value	0.001 (0.36)	0.0002 (0.70)	0.0001 (0.87)	-0.0002 (0.64)
$e_{2t}e_{3t}$ p-value	0.03 (0.62)	0.05 (0.42)	0.003 (0.96)	-0.035 (0.48)
$e_{2t}e_{4t}$ p-value	-0.003* (0.03)	-0.002 (0.27)	0.0003 (0.86)	-0.0001 (0.91)
$e_{3,t}{}^2$ p-value	0.03* (0.00)	0.022* (0.00)	-0.007 (0.34)	0.029* (0.00)
$e_{3t}e_{4t}$ p-value	-0.003 (0.46)	0.002 (0.56)	-0.001 (0.73)	-0.014* (0.00)

$e_{4,t}^{2}$ p-value	0.0001 (0.90)	0.002* (0.05)	0.0023 (0.06)	-0.001 (0.22)

* significant up to 5% significant levels.

6. Concluding remarks:

This paper investigates volatility transmission between food commodity prices of wheat and corn, and inputs prices of crude oil and fertilizers. The corn commodity is taken here to assess the impact of change in demand for biofuel on food commodity markets. Results of multivariate GARCH model indicate volatility in corn price transmit to wheat price changes. Also indicated that while volatility in wheat and corn markets is influenced by shocks (unexpected news) in oil market, the effect of crude oil price changes on corn and wheat markets is insignificant. This result signify the impact of speculation in food commodity prices. The impulse response analysis indicate shocks in oil markets have permanent effect on food commodity price changes. Also indicated that volatility in fertilizers markets transmit to wheat and corn markets. Thus, shocks in crude oil markets have direct and indirect effects (via fertilizers markets) on food commodity markets. Also indicated that volatility in fertilizers markets is influenced by volatility in the food commodity prices and oil prices, as both covariance terms $(h_{12,t} \text{ and } h_{13,t})$ are significant and positive. Fertilizers markets are also affected by own-shocks and shocks in crude oil markets, as both $(e^2_{1t} \text{ and } e^2_{3t})$ significant and positive.

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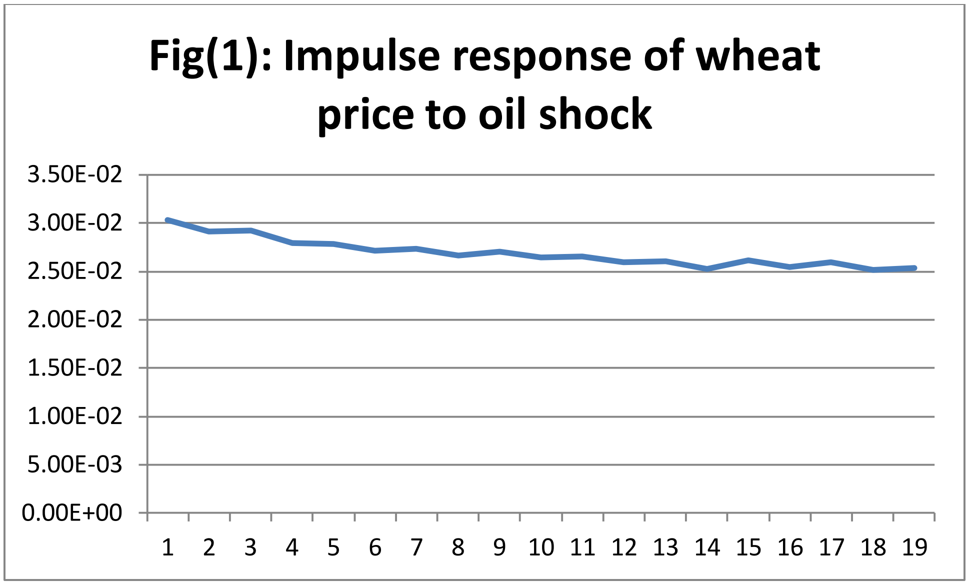
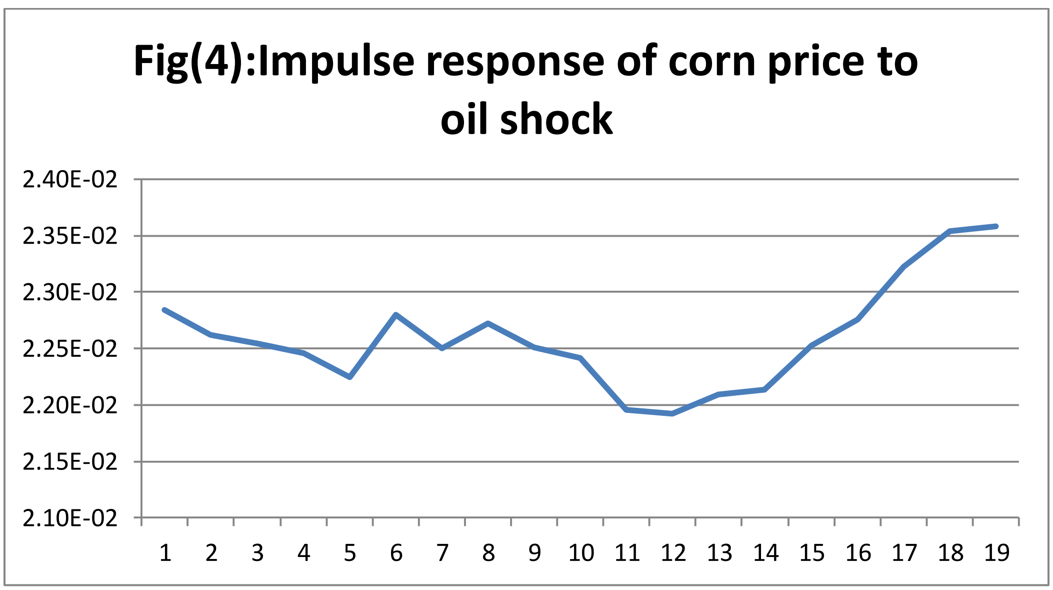

Fig(1): Impulse response of wheat price to oil shock
3.50E-02
3.00E-02
2.50E-02
2.00E-02
1.50E-02
1.00E-02
5.00E-03
0.00E+00
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19


Fig(4):Impulse response of corn price to oil shock
2.40E-02
2.35E-02
2.30E-02
2.25E-02
2.20E-02
2.15E-02
2.10E-02
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19