Do Crude Oil Price Levels Or Its Volatility Matter In Global Food Commodity Price Change?

***Ibrahim Onour**
School of Management Studies, University of Khartoum, Khartoum, Sudan.

***Correspondence:** ibonour@hotmail.com, onour@uofk.edu

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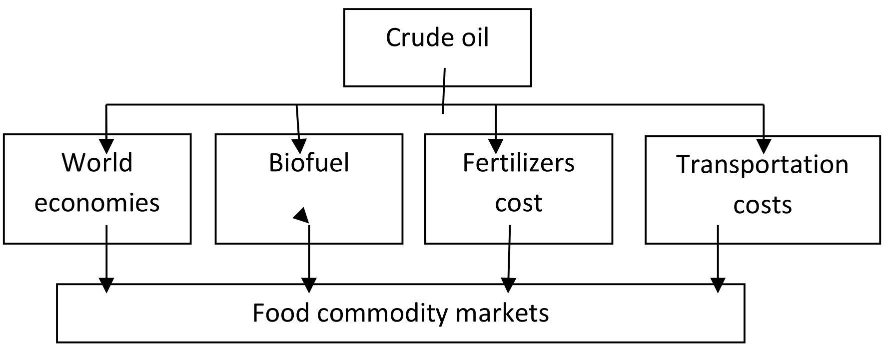
ABSTRACT
This study investigates the effect of crude oil price fluctuations on wheat, sugar, corn, and fertilizers. Results of Markov switching dynamic regression support evidence of two states. State 1, pertains to the low volatility of crude oil prices, and state 2, refers to higher volatility of crude oil prices. At state 1 higher levels of oil prices lead to a decline in food commodity prices, whereas in state 2, higher oil prices cause an increase in food commodity prices. Results of Dynamic Conditional Correlation (DCC) GARCH estimates indicate the coefficients of oil price levels are significant and positively associated with the conditional volatility of the four commodity prices, implying that fluctuations in global food commodity prices are not due to oil price volatility but due to the oil price levels attained at the extreme points.

KEYWORDS: Crude Oil; Food Commodities; Volatility; GARCH.

1. INTRODUCTION

The rise in the global food prices that began in 2006 set off a surge of food price inflation around the world, causing food insecurity that triggered violent protests in a number of countries across the world. Africa was perhaps most affected, despite the problem was global. Studies (FAO, 2011) on the impact of high food prices on the poor across several developing countries led to calls for international policy actions that absorb the negative effect on poverty and malnutrition increase. Some authors (Onour, 2010) attribute the main cause of global food commodity prices rise to crude oil price rises, via multiple transmission venues. The transmission effect of crude oil prices on global food prices can pass through multiple routes. Oil price rise can transmit to food markets directly, via shipment and transportation costs rise, or indirectly in the form of increased demand for cereals (corn and sugar cane) for biofuel production purposes, and also by raising the cost of fertilizers (Figure 1). Another factor attributed to global food commodity prices rise in the past decade is the depreciation of the US dollar, in which international prices of crude oil prices tend to be denominated (Hudson, 2009). An explanation of global food commodity price increases attributed to increased demand for certain agricultural commodities used for feedstocks for biofuel production, particularly maize or sugar cane for ethanol. Also, an explanation of food commodity price increase is attributed to the rapid economic growth in certain emerging economies, notably China and India, for livestock products, and demand rise for food which generated increased cereal and oilseed demand for feed. These explanations suggest a structural change in global food commodity prices due to fundamental new drivers that may persist for quite a long time in the future.

Figure 1: Crude oil price transmission effect.



The current paper adds to the existing literature by answering the following two questions. What is the impact of crude oil price fluctuations on the agricultural food commodity price changes? Does oil price volatility or its extreme price levels that matter more in the agricultural commodity price fluctuations?

The remaining parts of the paper are structured as follows: section two highlights the literature review, section three illustrates the methodology of the research, section 4 discusses the empirical results, and the final section concludes the study.

2. LITERATURE REVIEW

Deaton and Laroque (1991) have investigated 95 agricultural and oil commodities price transmission mechanisms and market integration using a storage model to find out that prices are not normally distributed, as the stockholding behavior of risk-averse agents generates autoregressive pattern behavior. Depreciation of the dollar value and speculations in future markets are additional factors that may influence agricultural commodity price movement (Trostle, 2008). Also had been found that the impact of higher energy prices can be reflected in higher farm production costs causing lower growth in agricultural production and yield (Tyner and Taheripour, 2008). The indirect effect of energy price rise includes diversion of land under crops for use of other agricultural energy-related crops (sugar and corn), reducing their supply, and driving up their prices (Schmidhuber, 2007). The expansion in biofuels production was an important driver behind corn and oilseed demand growth (Zhang *et al*., 2010; Ciaian and d'Artis, 2011). Biofuel policies, encouraging farmers to produce feed-stocks for biofuel purposes, have increased dependency between energy prices and agriculture prices (Gohin and Chantret, 2010; Nazlioglu, 2011). The question that, to what extent food commodity prices are unduly volatile and unconnected to the market fundamentals has been investigated extensively by Balcombe (2009, 2013). The persistence of non-fundamental effects on food prices has been considered by Serra and Gil (2012). In presence of volatility overshooting above what can be accounted for by changes in market fundamentals, indicates commodity prices may reflect inefficient signals for resource allocation (Balcombe and Fraser, 2013). It is important to realize that time-varying volatility of prices in general, as addressed by Myers (1992), has an effect on statistical inference as the existence of heteroscedasticity, causing loss of efficiency and biasedness of estimated standard errors. Furthermore, excess kurtosis causes additional problems as inference theory requires assumptions of normal distribution of the error terms, despite the actual distribution of prices appears to have fatter tails than the normal. This creates a problem in the maximum likelihood estimation of commodity market models (Myers, 1992).

3. METHOD(S)

To estimate the effect of crude oil price volatility transmission to major food commodity prices in this paper we employed dynamic conditional correlation (DCC) multivariate generalized autoregressive conditionally heteroskedastic (MGARCH) model. The general specification of the DCC-MGARCH model, as developed by Bollerslev *et al.* (1988) is:

$$y_t = CX_t + e_t \qquad (1)$$

$$e_t = H_t^{1/2} v_t \qquad (2)$$

$$H_t = D_t^{1/2} R_t D_t^{1/2} \qquad (3)$$

$$R_t = diag\left(Q_t^{-\frac{1}{2}}\right) Q_t diag\left(Q_t^{-\frac{1}{2}}\right) \qquad (4)$$

$$Q_t = (1 - \mu_1 - \mu_2)R + \mu_1 e_t e'_{t-1} + \mu_2 Q_{t-1} \qquad (5)$$

Where

y_t is $(mx1)$ vector of dependent variables

C is (mxk) matrix of parameters

X_t is $(kx1)$ vector of independent variables which may contain lags of y_t

$H_t^{1/2}$ is the Cholesky factor of the conditional covariance matrix H_t

v_t is $(mx1)$ $vector$ of $independent$ and $identically$ $distributed$ $innovations$

D_t is a diagonal matrix of conditional variance in which each

$$\sigma_{i,t}^2 = s_i + \sum_{j=1}^{pi} \alpha_j e_{i,t-1}^2 + \sum_{j=1}^{qi} \beta_j \sigma_{i,t-j}^2$$

R_t is a matrix of conditional quasicorrelation.

4. EMPIRICAL ANALYSIS

The study employs monthly price series for five commodities that include, wheat, sugar, corn, fertilizers, and crude oil prices during the sample period from January 1988 to April 2018 (360 observations[1]). Plots of the price series, included in the appendices (A1–A5), indicate there are two distinct states, for all the five commodities, a state of relatively low variability of prices, and a state of high variability. A striking feature about the price changes of the food commodities is that the high volatility period covers the time from 2006 to 2014, and the high volatility period for the oil price extend from 2004 to 2014, which is an indication that crude oil price is the common factor that influences these food commodity prices. To investigate more formally the pattern of price changes of food commodities and crude oil prices, we employed Markov switching dynamic regression to assess the transition probabilities that decompose the pattern of price changes into different states. Results of Markov switching regression support evidence of two states, which are in line with the two states indicated in the graphical plots in the appendix. To distinguish the behavior of oil price fluctuations in the two states we regressed change in oil prices on time variable (the trend) and oil price levels. Regression results (Table 1) reveal that state 1 corresponds to the time where oil price change follows a trend line (significance of the coefficient of the time variable), but in state 2 the trend variable is insignificant. Looking at Figure (1) above it becomes clear that state 1 refers to the period where a visible trend pattern can be observed for oil price changes, and that refers to the period extending from 1988 to 2005. Markov switching results indicate in state 1, for all food commodities, the coefficients of oil price levels are significant and negatively associated with the change in food commodity prices, implying that higher levels of oil prices in this period (state 1) induce a decline in food commodity prices, and the opposite is true for lower oil price levels. However, in state 2, the coefficients of oil price levels are significant and positively associated with a change in the food commodity prices, implying that higher oil price levels correspond to an increase in food commodity prices, and the opposite is holding at lower oil price levels. These results support a piece of evidence that the impact of oil prices on global food commodity prices differs depending on the size of oil price volatility. The transition probability of having state 1 an absorbing state, p11=0.91, for wheat and corn commodities implies, given the prices of these two commodities are in state 1 then there is a very high probability of staying in the same state at any subsequent period. However, the transition probabilities for the same two commodities of changing from state 2 to state 1 (p21) are respectively 0.80 and 0.66 indicating that price change from one state to another is still very high for the wheat compared to the corn prices. But once the prices of the two goods are in state 2, then there is a very small chance to stay in the same state for quite a long period, as indicated by the small probabilities of p22 for each of the two commodities at 0.20 and 0.44 respectively. However, the situation is quite different for the other two commodities, sugar and crude oil, which reveal state 2 is an absorbing state, as indicated by the high transition probabilities of p22 of each commodity price at 0.90 and 0.98 respectively. Since there is a high probability of staying in state 1, if initially in state 1 for wheat and corn commodities, and also high probabilities of staying in state 2 if initially in state 2, for the sugar and crude oil, then the important question is, what is the duration of each of these states for each commodity? Results of transition probabilities in Table 1 imply that for wheat and corn commodities the duration of remaining in state 1 on average is about one year (11 months), and for the sugar and crude oil the duration of remaining in state 2 is about 10 months for the sugar and 50 months for crude oil.

To estimate the impact of the oil price effect on food commodity prices, we employed the dynamic conditional correlation (DCC-GARCH) model. Since conditional volatility models, in general, are sensitive to unit root, we checked all price series for the Phillip-Perron unit root test reported in Table 2 and show that price levels of the four commodities are non-stationary and therefore unpredictable, but their changes are stationary or predictable because they are mean-reverting.

[1] All data gathered from index mundi website.

Table 1: Markov-Switching Dynamic Regression[2].

Variables	Coef	p-value	Variables	Coef	P-value
<u>State 1</u>			<u>State 1</u>		
Δ wheat:			Δ corn:		
Δ oil	0.14	0.40	Δ oil	0.52	0.000*
oil	-0.06	0.007*	oil	-0.05	0.004*
Constant	1.64	0.65	onstant	1.50	0.100
<u>State 2</u>			<u>State 2</u>		
Δ wheat:			Δ corn:		
Δ oil	3.09	0.000*	Δoil	0.87	0.000*
oil	0.56	0.000*	oil	0.30	0.004*
constant	-11.3	0.11	constant	-6.14	0.10
LL= -1413			LL= - 1585		
AIC=7.90			AIC=8.8		
P11=0.91			**P11=0.91**		
P21=0.80			**P21=0.66**		
P12=0.08			**P12=0.09**		
P22=0.20			**P22=0.44**		
<u>State 1</u>			<u>State 1</u>		
Δ sugar:			Δ oil:		
Δoil	-0.07	0.63	time	0.13	0.000*
oil	-0.57	0.09	oil Constant	0.09	0.009*
Constant	9.55	4.97	<u>State 2</u>	-57.6	0.000
<u>State 2</u>			Δoil		
Δsugar:			time		
Δoil	0.16	0.63	oil	-0.002	0.27
oil	0.12	0.001*	constant	0.038	0.000*
Constant	-1.89	0.30	LL = -944	-0.40	0.22
LL =-1567			AIC= 5.31		
AIC=8.7			**P11=0.69**		
P11=0.45			**P21=0.02**		
P21=0.10			**P12=0.31**		
P12=0.55			**P22=0.98**		
P22=0.90					

*Significant at 1% significance level. **significant at 5% sig. level.
Note: Pij computed using P11+P12=1, and P21+P22=1.

Table 2: Phillip-Perron unit root test.

Variable	Test stat*	Decision**
<u>Level:</u>		
Wheat	2.21	No rejection of unit root
Sugar	2.08	No rejection of unit root
Crude oil	1.79	No rejection of unit root
corn	2.74	No rejection of unit root
<u>1st difference</u>:		
Wheat	73.06	Rejection of unit root
Sugar	67.6	Rejection of unit root
Crude oil	47.6	Rejection of unit root
corn	57.14	Rejection of unit root

*PP test constant with the trend
**5% sig. level critical value is 4.68

[2] mswitch fits dynamic regression models that exhibit different dynamics across unobserved states using state-dependent parameters to accommodate structural breaks or other multiple-state phenomena. These models are known as Markov-switching models because the transitions between the unobserved states follow a Markov chain.

Dynamic Conditional Correlation GARCH model in Table 3 reveals the mean effect of oil price changes and its price level on food commodity price changes, as well as the impact of oil price level on commodities price volatility as represented by GARCH (conditional volatility) effect on the four commodity prices. DCC estimation results show neither fluctuations in oil prices nor oil price levels have a statistically significant impact on change in food commodity prices. However, oil price levels influence significantly the volatility of food commodity prices. As the coefficients of oil prices are significant and positively associated with the conditional volatility of food commodity prices, implying that higher levels of oil prices, increase the volatility of food commodity prices. In other words, fluctuations in global food commodity prices are not due to impacts of oil price volatility but due to the price levels attained at the extreme points.

Table 3: DCC MGARCH model: The impact of oil prices on commodity prices.

Variables	Coefficient	Std. err.	p-value	Variables	Coefficient	Std. err.	p-value
Δ Wheat price				Δ Corn price			
Δ oil price	0.34	0.17	0.04	Δ oil price	0.127	0.14	0.39
Oil price	0.004	0.02	0.84	Oil price	0.009	0.019	0.62
Constant	-0.41	0.87	0.64	Constant	-0.291	0.63	0.64
Volatility:				Volatility:			
ARCH :				ARCH:			
L1	0.27	0.099	0.005*	L1	0.44	0.11	0.000*
L2	0.26	0.095	0.005*	L2	-0.23	0.100	0.022
GARCH:				GARCH:			
L1	0.14	0.094	0.13	L1	0.56	0.147	0.000*
oil price	0.027	0.003	0.000*	oil price	0.031	0.003	0.000*
constant	2.68	0.26	0.000*	constant	1.39	0.396	0.000*
Δ Sugar price				Δ Fertilizers price			
Δ oil price	0.34	0.25	0.16	Δ oil price	0.49	0.25	0.057
Oil price	-0.04	0.03	0.28	Oil price	0.03	0.04	0.34
Constant	0.71	1.15	0.54	Constant	-1.49	1.11	0.18
Volatility:				Volatility:			
ARCH:				ARCH:			
L1	0.25	0.10	0.015	L1	0.218	0.10	0.031
L2	-0.85	0.08	0.32	L2	0.116	0.09	0.24
GARCH:				GARCH:			
L1	0.72	0.109	0.000*	L1	0.47	0.09	0.000*
oil price	0.02	0.004	0.000*	oil price	0.04	0.004	0.000*
constant	2.22	0.58	0.000*	constant	2.09	0.34	0.000*

*Significant at 1% significance level.

6. CONCLUSION

Change in oil price is frequently used as a predictor of change in food commodity prices as well as a variable of impact on transition probabilities. To investigate the pattern of price changes of food commodities, we employed Markov switching dynamic that decomposes the pattern of price changes into different states. Results of Markov switching regression support evidence of two states. Results of Markov switching dynamic regression support evidence of two states, and indicate that in state 1, which pertain to the low volatility of crude oil price, higher levels of crude oil prices lead to a decline in food commodity prices, whereas in state 2, which refers to higher volatility of crude oil price, higher oil price levels cause an increase in food commodity prices. These pieces of evidence support the conclusion that the impact of oil prices on global food commodity prices depends on different states of oil price volatility. The transition probabilities indicate when the prices of wheat and corn are in state 1, there is a very high probability of remaining at the same state in any subsequent period. Thus, state 1 is an absorbing state for wheat and corn, but for sugar and fertilizers, state 2 is absorbing. Regarding the duration of each of these states, our findings indicate for wheat and corn commodities the duration of remaining in state 1 on average is about one year (11 months), whereas for the sugar and fertilizers the duration of remaining in state 2 respectively about 10 months and 50 months. Results of Dynamic Conditional Correlation (DCC) GARCH estimates indicate the coefficients of oil price levels are significant and positively associated with the conditional volatility of the four commodity prices, implying that fluctuations in global food commodity prices are not due to oil price volatility but due to the oil price levels attained at the extreme points.

CONFLICT OF INTEREST

None.

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Appendix

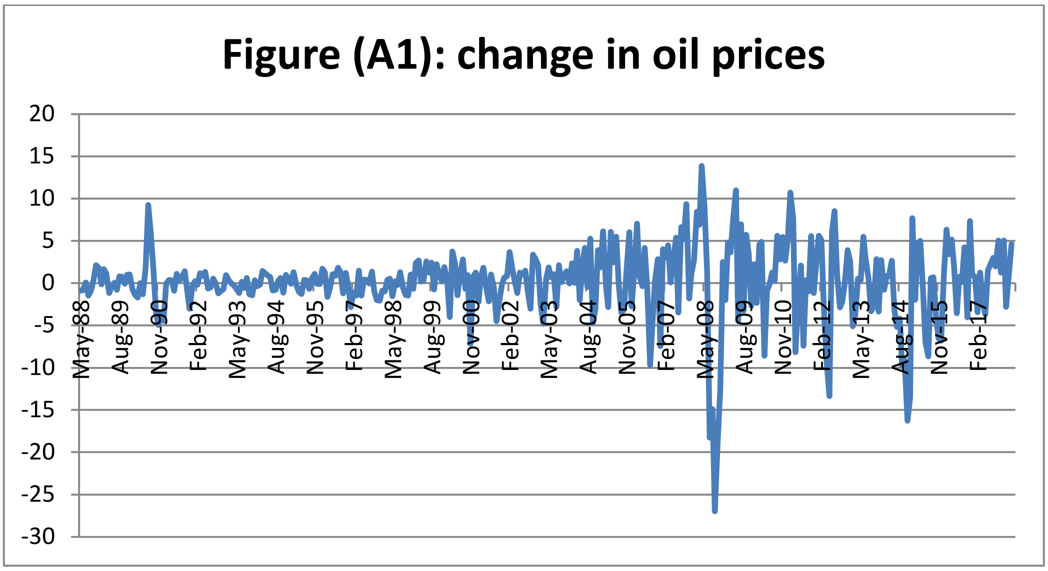


Figure (A2):change in wheat prices

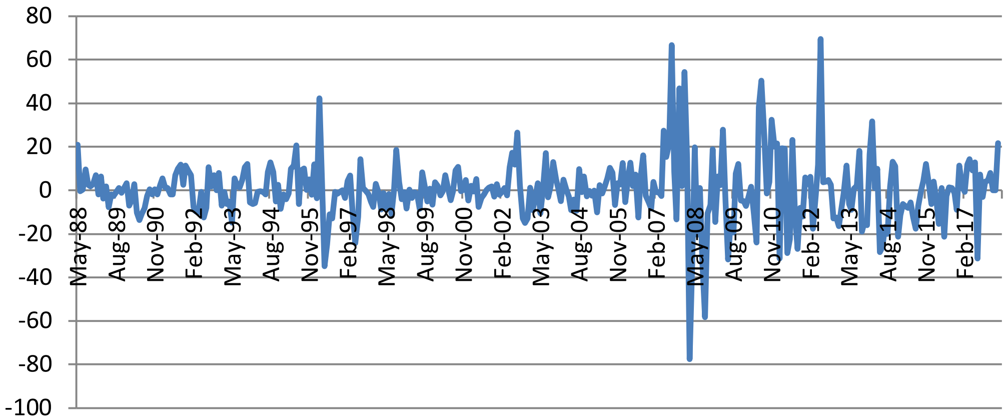


Figure (A3): change in sugar prices

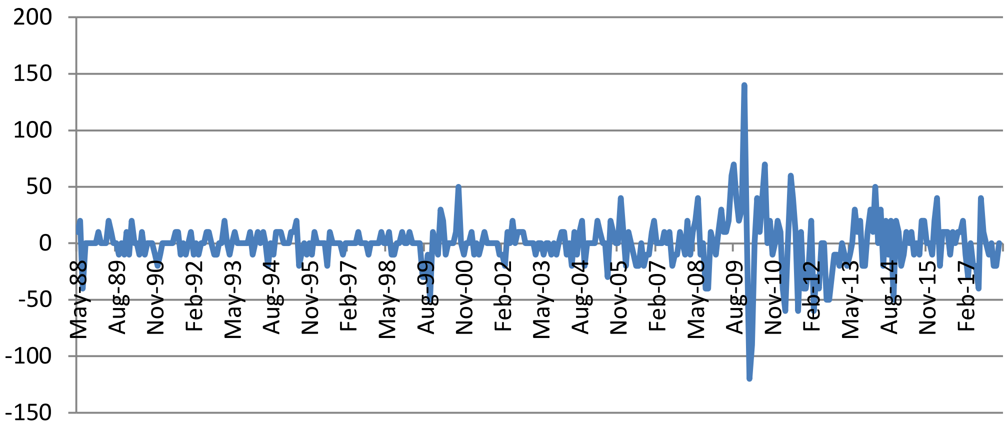
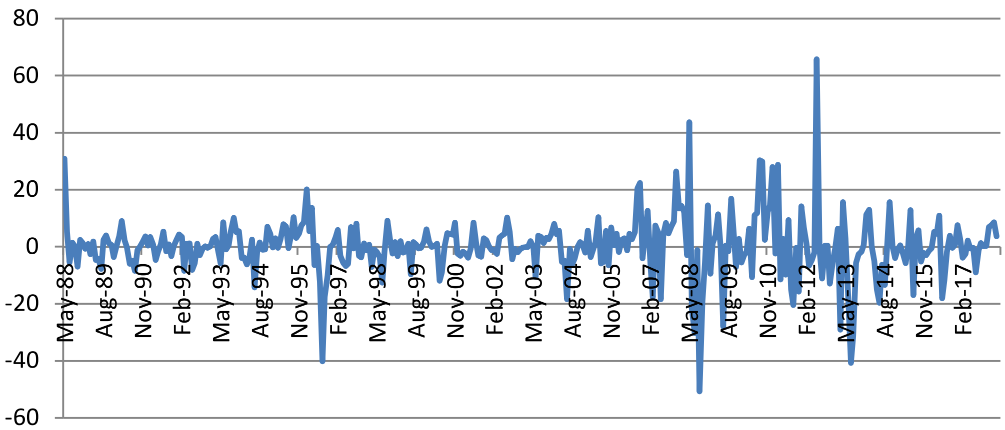


Figure (A4): change in corn prices



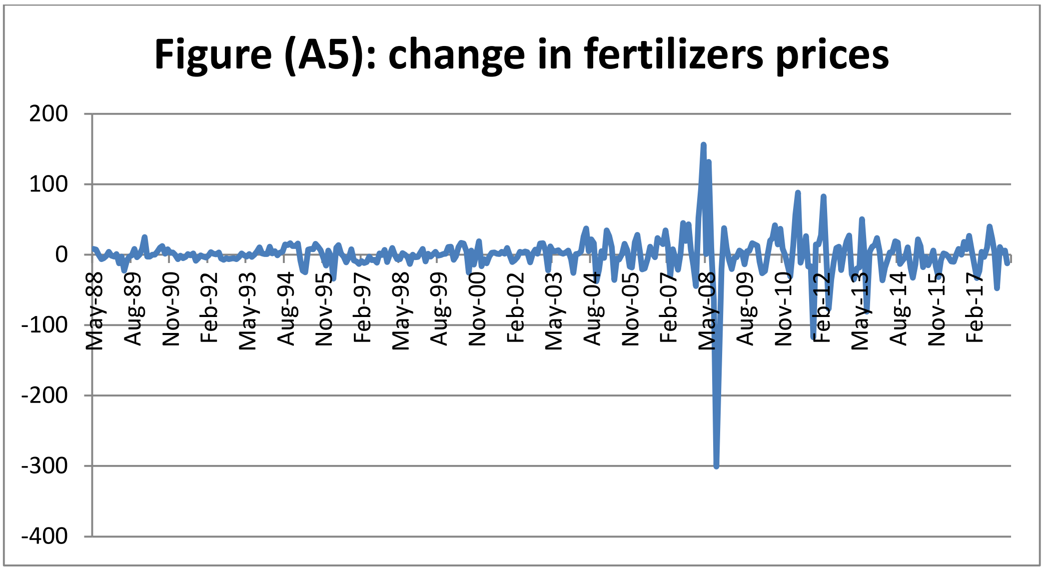


Figure (A5): change in fertilizers prices
200
100
0
-100
-200
-300
-400
May-88
Aug-89
Nov-90
Feb-92
May-93
Aug-94
Nov-95
Feb-97
May-98
Aug-99
Nov-00
Feb-02
May-03
Aug-04
Nov-05
Feb-07
May-08
Aug-09
Nov-10
Feb-12
May-13
Aug-14
Nov-15
Feb-17