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Impact of Energy Price Variability on Global Fertilizer Price: Application of Alternative Volatility Models

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Abstract

This study evaluates the effects of volatility in crude oil and natural gas prices on fertilizer price variations. Specifically, the study looks at the mean and volatility effects of oil and natural gas prices on both mean and volatility changes in fertilizer prices. Both symmetric models [GARCH (1, 1)] and asymmetric models [GJR (1, 1)] were used to model volatility in fertilizer prices and to evaluate the effects of the volatility over different time periods using Bai-Perron structural break tests. The results show that changes in oil and natural gas prices increased fertilizer prices after the crisis period, during June 2007 to June 2008. Both the ARCH and GARCH had significant effects on fertilizer prices, suggesting that the volatility effects of oil and natural gas prices on fertilizer prices were also significant. Furthermore, the maximum impact of higher energy prices depends on triple superphosphate and diammonium phosphate (DAP) leading to higher production costs and consequent increase in total farm expenditures for crop producers. These higher production costs invariably have a negative effect on farm profitability, thus reducing the investment levels in the farm sector.

Keywords: Oil Price Volatility, Global fertilizer price volatility, Bai-Perron Structural break test, Natural gas price volatility

1. Introduction

1.1 Introduce the Problem

Fertilizers are combinations of nutrients that enable plants to grow. The essential elements of fertilizers are nitrogen, phosphate, and potassium. Almost all nitrogen fertilizer is derived initially from anhydrous ammonia (NH_3), which is made by reacting atmospheric nitrogen and hydrogen from natural gas. The cost of natural gas accounts for 70% to 90% of the production costs of ammonia (Kenkel, 2010). As energy prices increase, the price of ammonia increase as producers competes with other industries for their gas supply. The production of phosphate fertilizer begins with mining rock phosphate. Potassium fertilizers come from mining potash ore deep in the earth. Although there is some potash production in New Mexico and Utah, most potash is imported from Canada. Prices of nitrogen, phosphate, and potassium fertilizers began increasing in 2002 and reached historic highs in mid-2008. During the 12-month period between June 2007 and June 2008, nitrogen, DAP, and potash prices increased by 59%, 359%, and 173% respectively (Huang, 2009).

Over the past decade, owing to higher demand for biofuels and feedstock as well as higher demand for renewable energy, there have been greater linkages between the agriculture and energy markets. The underlying causes of fertilizer price volatility include a shift to a global supply chain, an increase in the production of biofuel, the volatility of prices of raw materials (such as natural gas), and the volatility in exchange rates (Beckman et al., 2013).

This paper investigates the relationship in the volatility of natural gas, crude oil, and global fertilizer prices. As volatility involves financial risks, the results provide useful information for optimum energy use, global agricultural production, and profitability of the farm sector. The remainder of the paper is organized as follows: In the next sub-section, we provide the importance of this problem. This is followed a relevant discussion of the literature. Section 2 develops the method and the hypotheses that are tested. Section 3 discusses the main results of the paper. This is followed by discussion of the results along with the main policy implications of the study.

1.2 Importance of the Problem

Over the past decade, rising energy prices coupled with evolving policies promoting renewable energy and on-farm conservation practices have transformed the relationship between the energy and agriculture sectors (Beckman et al., 2013). Agriculture uses energy both directly in the form of fuel and electricity and indirectly through the use of energy-intensive inputs, such as fertilizers and pesticides. However, over the past decade, record-high energy prices and expanding biofuel production have increased the demand for agricultural commodities and have also increased the demand for biofuels and feedstocks. In this context, several recent studies have examined the relationship between fertilizer markets, commodity markets, and energy markets and how this relationship has evolved over time. No definitive answers can be given on the transmission mechanisms of how one market affects other markets, as the literature is still evolving. Thus, an empirical examination of the linkages between oil and natural gas prices on different fertilizer prices is important. Previous literature has examined only the linkages in mean and volatility effects of oil prices on fertilizer prices. An important determinant of fertilizer prices, namely natural gas price effects is thus missing from the empirical literature. We contribute to the existing studies by looking at the mean and volatility effects of oil and natural gas prices on various fertilizer prices over the period December 1993 to January 2012. In addition, we conduct structural break tests to identify the crisis periods (namely June 2007 to June 2008), where fertilizer price volatility was significant. Finally, we validate our model using ARCH/GARCH models and demonstrate why these models are relevant for understanding the volatility in fertilizer prices.

1.3 An Overview of the Literature

Interest in studying fertilizer price volatility and forecasting begins in the early 1990s. During the mid-1970s and throughout the 1980s, U.S. fertilizer prices were highly volatile. We discuss only the relevant literature for the past five years.

Galbraith (2010) used an error correction model to determine how anhydrous ammonia (AA) and urea prices at different locations in North America adjusted to changes in crop and input prices during two time periods – 2002 to 2005 and 2006 to 2009. Galbraith also considered measures of supply and demand shocks such as natural gas price futures as a measure of supply shock and corn futures as a measure of demand shock. The empirical results suggest that natural gas future prices had relatively more of an impact on nitrogen fertilizer prices during the 2002 to 2005 period. In addition, nitrogen prices tended to adjust more rapidly to increases in natural gas futures prices than decreases. In the 2006 to 2009 period corn futures prices had more of an impact on nitrogen prices. Nitrogen prices tended to respond immediately to decreases in corn futures prices. The nitrogen price responses to increasing corn futures prices were mixed.

Ott (2012) analyzes the drivers behind the recent price volatility of fertilizers and their interplay with energy and food commodity market prices. Three issues are examined: the role of speculations for fertilizer price formation; the interaction among fertilizers, food, and energy prices; and fertilizer price volatility. First, the results showed the presence of speculative behavior in fertilizer markets. However, the speculation on derivative markets was not the cause. Instead the volume traded in the physical markets was the driver behind the volatility in fertilizer markets. It is likely that fertilizer derivative products may have been used as hedging tools and not as speculative ones. Second, the prices of food commodities were driving the fertilizer markets and not vice versa. In addition, higher food prices induced a higher demand for fertilizers, thus increasing food prices to higher levels. Third, the energy sector influenced the increase in fertilizer prices through the input cost channel. For example, rising oil and natural gas prices contributed to a demand for nitrogen nutrients, the production of which depends significantly on energy inputs for production and transport. Fourth, given the oligopolistic fertilizer supply chain and inelastic supply, the upward spiral in fertilizer prices was also due to uncertainty caused by the low levels of inventory. In other words, over the past 15 years, the excess nitrogen supply has disappeared while phosphate and potash supply remained at marginal levels. This implied that no buffer could protect the fertilizer markets when an adverse shock occurred in 2007. Finally, the results show the volatility of energy, food, and fertilizer prices moved closely together when energy prices were increasing. However, when energy prices were declining, food and fertilizer price volatility did not move together, showing that there were asymmetries in the price volatility.

Du and McPhail (2012) examine the co-movement and increasing volatility of ethanol, gasoline, and corn prices over the period, March 2005 to March 2011. A structural change was identified around March 2008 in the pairwise dynamic correlations between the prices using a multivariate GARCH model. A structural vector autoregression model (VAR) model is then estimated on two subsamples, one before and one after the identified change point. Variance decomposition analysis was conducted to examine the channels of variance transmission.

The results of the study show that first, during the earlier period, the responses in one market to price changes in another market were not statistically significant, implying that price variations of individual markets were largely independent and explained by their own shocks. Second, in contrast to the first period, during the second period, all the prices were closely linked due to a strengthened corn-ethanol relationship. Variance decomposition analyses showed that for each market a significant and relatively large share of the price variation could be explained by the price changes in the other two markets. The ethanol shocks had the largest impact on corn prices, suggesting a strong linkage between corn and ethanol markets. The results are robust to the inclusion of the seasonal dummies and various macro and financial indicators.

Chen et al. (2013) empirically evaluate the effect of crude oil prices on global fertilizer prices, both in mean and volatility. Weekly data for the period 2003 to 2008 were used for this analysis. Using descriptive statistics, the results found three time periods with two structural breakpoints in the data for six global fertilizer prices and crude oil prices. Using the Granger causality test, the results showed that most global fertilizer prices were influenced by the crude oil price. The empirical results further demonstrated that crude oil prices had relatively larger effects on global fertilizer prices during the second time period (i.e., after 2008). Thus the sensitivity of fertilizer prices to oil prices increased and became statistically significant. For example, the impact of oil price on the monoammonium phosphate (MAP) price is 1.25% during the first period, 4.9% during the second period, and 6.4% during the third period. This sensitivity may explain why global fertilizer prices reached a peak in 2008, as the crude oil prices reached a high level during the same period.

Various models (including generalized autoregressive conditional heteroskedastic (GARCH), GJR (Note 1), and EGARCH (Note 2)) were selected and estimated on the basis of the Schwartz-Bayes (BIC) criterion and the regularity conditions of the quasi-maximum likelihood estimators to be consistent and asymptotically normal. The main result of the study is that crude oil prices exert a greater impact on fertilizer prices during the latter part of 2008. This result may suggest that as the volatility in global fertilizer prices has increased, vital energy prices and agricultural production are likely to be significantly affected. This may lead to future instability in agricultural commodity prices. Thus it is important to understand the directional relationship between the volatility in energy and global fertilizer prices.

1.4 Hypotheses and Research Design

We specify an ARDL model, since it is likely to explain the short-run dynamics between energy prices and the fertilizer prices.

A general ARDL model for a global fertilizer price can be written as follows:

$$FP_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \, FP_{t-i} + \sum_{j=1}^{q} \beta_j \, oilP_{t-j} + \sum_{k=1}^{r} \gamma_k NGP_{t-k} + u_t \qquad (1) \text{ (Note 3)}$$

In Equation (1), the coefficient β_j denotes the effect of the j^{th} period lagged crude oil price on the fertilizer price, which means that the fertilizer price can be predicted by the crude oil price. Similarly the coefficient γ_k denotes the effect of the k^{th} period lagged natural gas price on the fertilizer price. FP denotes the respective fertilizer price series. A test of the null hypothesis that each $\beta_j = 0$ and $\gamma_k = 0$ is a test of Granger non-causality.

All the prices in the model should be stationary series to avoid spurious regression results, whereby the asymptotic standard normal results no longer hold. For this reason, the structural breakpoints of the fertilizer prices are estimated using the Bai-Perron tests as discussed in Section 2.2. If and when the appropriate structural breakpoints are found, the fertilizer price equations will be estimated for different periods.

2. Method

The stationary AR(1)-GARCH(1,1) model is considered for understanding the volatility in global fertilizer price data on the lines of Engle (1982).

2.1 Conditional Mean and Conditional Volatility Models

Let the *AR(k*) process for the fertilizer price series z_t be defined as:

$$z_t = \varphi_1 + \sum_{i=1}^{k} \omega_i z_{t-i} + \varepsilon_t; \; = 1, \ldots\ldots, k; \; t = 1, \ldots\ldots T; \; \varepsilon_t \sim IID(0, \sigma^2); \; |\omega_i| < 1 \qquad (2)$$

z_t denotes the fertilizer price, φ_1 is the constant parameter affecting fertilizer prices, z_{t-i} denotes the autoregressive components of fertilizer price series, ω_i represents the autoregressive parameters, and ε_t is the error term. In Equation (2) z_t is assumed conditional on the "immediate past information set" Ω_{t-1}, and thus its conditional mean can be expressed as:

$$E(z_t | \Omega_{t-1}) = \varphi_1 + + \sum_{i=1}^{k} \omega_i z_{t-i} \qquad (3)$$

Equation (3) shows that the conditional mean of z_t is time-varying and this is a characteristic of financial time series. Following Engle (2002), the error term is as follows:

$$\varepsilon_t = \mu_t\left(\beta_0 + \sum_{j=1}^{q} \beta_j \varepsilon_{t-j}^2\right) \;;\; j = 1, \ldots \ldots q \tag{4}$$

Equation (4) is the ARCH(q) model proposed by Engle.

Equivalently, equation (4) may be expressed as:

$$\varepsilon_t^2 = \mu_t^2\left(\beta_0 + \sum_{j=1}^{q} \beta_j \varepsilon_{t-j}^2\right) \tag{5}$$

Taking the expectation of Equation (5) given the relevant information set (π_{t-1}), the conditional variance is given as:

$$var(\varepsilon_t|\pi_{t-1}) = \beta_0 + \sum_{j=1}^{q} \beta_j \varepsilon_{t-j}^2 \text{ since } E(\mu_t^2|\pi_{t-1}) = 1 \tag{6}$$

Equation (6) defines an alternative formulation of the ARCH(q) model, where the $var(\varepsilon_t|\pi_{t-1})$ is a function of the squared error term from past periods ε_{t-j}^2.

In the case of unconditional variance, using the lag operator L, equation (6) becomes:

$$\sigma_t^2 = E(\varepsilon_t^2) = \frac{\beta_0}{1-\beta(L)} \tag{7}$$

where, $\sum_{j=1}^{q} \beta_j \varepsilon_{t-j}^2 = \beta(L)\varepsilon_t^2$ and $\beta(L)$ is the polynomial lag operator $(\beta_1\mathrm{L} + \beta_2\mathrm{L}^2 + \cdots + \beta_q\mathrm{L}^q)$

The null hypothesis to be tested based on equation (7) is given by:

$$H_0: \beta_1 = \beta_2 = \cdots = \beta_j = 0$$

This hypothesis is tested using either the F-test or nR^2 that follows the Chi-square distribution proposed by Engle (1982). If the null hypothesis is not rejected, then there is no ARCH effect in the model and vice versa.

Engle's ARCH model was extended by Bollerslev (1986), which extends equation (6) by incorporating the lags of the conditional variance equation:

$$\sigma_t^2 = \beta_0 + \sum_{j=1}^{q} \beta_j \varepsilon_{t-j}^2 + \sum_{i=1}^{p} \gamma_i\, \sigma_{t-i}^2 \tag{8}$$

where, p≥ 0; q> 0; β_0> 0; $\beta_j \geq 0$; $\gamma_i \geq 0$, *j= 1,……..,q* and *i= 1, …….,p*

Equation (8) is the GARCH *(p,q)* model where *p* and *q* denote the lagged terms of the conditional variance and the squared error term respectively. The ARCH effect is denoted by $\sum_{j=1}^{q} \beta_j \varepsilon_{t-j}^2$ and the GARCH effect is denoted by $\sum_{i=1}^{p} \gamma_i\, \sigma_{t-i}^2$.

The asymmetric effects not accounted for in the ARCH and GARCH models is also taken into account. Nelson (1991) proposed the EGARCH (*p,q)* model as follows:

$$\log(\sigma_t^2) = \varphi_2 + [1 - \gamma(\mathrm{L})]^{-1}[1 + \beta(\mathrm{L})]\mathrm{f}\left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right) \tag{9}$$

and

$$\mathrm{f}\left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right) = \alpha\varepsilon_{t-1} + \theta\left(\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| - E\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right|\right) \tag{10}$$

In the EGARCH model, the log of the conditional variance term is a function of the lagged error term. The asymmetric effect is captured by the parameter α in equation (10). Asymmetric effect is present if $\alpha \neq 0$, and there is no asymmetric effect if $\alpha = 0$. The null hypothesis is $\alpha = 0$ and this is tested using the t-statistic.

The asymmetric effect can also be captured using the GJR-GARCH model, which modifies equation (8) as follows:

$$\sigma_t^2 = \beta_0 + \sum_{j=1}^{q} \beta_j \varepsilon_{t-j}^2 + \sum_{i=1}^{p} \gamma_i\, \sigma_{t-i}^2 + \sum_{j=1}^{q} \delta_j\, \varepsilon_{t-j}^2 I_{t-j} \tag{11}$$

where, $I_{t-j} = \begin{cases} 1 \; if \; \varepsilon_{t-j} > 0 \\ 0 \; otherwise \end{cases}$.

Thus, there is evidence of asymmetric effect if δ_j<(>)0, which implies that positive (negative) shocks reduce the volatility of z_t by more than negative (positive) shocks of the same magnitude.

2.2 Sequential Bai-Perron Tests for Structural Breaks

Ignoring possible structural breaks can lead to non-rejection of the null hypothesis of non-stationarity, so that the effects of structural breaks may be attributed to the existence of a unit root. For example, Nelson and Plosser (1982) used the Dickey-Fuller unit root test to examine U.S. macroeconomic time series and found the presence of widespread non-stationarity.

In this section a test of the null hypothesis of *l* breaks against the alternative that an additional break exists on the lines of Bai-Perron is considered. For the model with l breaks, the estimated breakpoints, denoted by $\widehat{t_1}, \dots\dots\dots\dots, \widehat{t_l}$, are obtained by a global minimization of the sum of squared residuals. This strategy proceeds by testing each (*l+1*) segment for the presence of an additional break by partitioning the time intervals $\widehat{t_1}, \dots\dots\dots\dots, \widehat{t_l}$. In other words, partitioning the sample space into two spaces and then applying the least squares over each of the partitioned sample space can allow us to determine the structural breakpoints in the model.

The test amounts to the application of (*l+1*) tests of the null hypothesis of no structural change against the alternative hypothesis of a single change. This test is applied to each segment containing the observations $\widehat{t_{\iota-1}} + 1$ to $\widehat{t_\iota}$ (*i= 1, ……, l+1*) using the convention that $\widehat{t_0} = 0$ and $\widehat{t_{l+1}} = t$. The model with *(l+1)* breaks is rejected if the overall minimum value of the sum of squared residuals over all segments where an additional break is included is sufficiently smaller than the sum of squared residuals from the *l* break model. The break date is the one associated with this overall minimum. This test is defined as:

$$F_t(l+1|l) = \left\{ S_t(\widehat{t_1}, \dots\dots\dots\dots, \widehat{t_l}) - \min_{1 \leq i \leq l+1} \inf_{\tau \in \omega_{i,\gamma}} S_t(\widehat{t_1}, \dots\dots\dots\dots, \widehat{t_{\iota-1}}, \tau, \widehat{t_1}, \dots\dots\dots\dots, \widehat{t_l}) \right\} / \widehat{\sigma^2} \quad (12)$$

where, $$\omega_{i,\gamma} = \left\{ \widehat{t_{\iota-1}} + (\widehat{t_\iota} - \widehat{t_{\iota-1}})\gamma \leq \tau \leq \widehat{t_\iota} - (\widehat{t_\iota} - \widehat{t_{\iota-1}})\gamma \right\} \quad (13)$$

$\widehat{\sigma^2}$ is a consistent estimate of σ^2 under the null hypothesis. (Note 4)

2.3 Data

Data on energy prices and fertilizer prices were obtained from various sources. The period of data collection was from December 1993 to January 2012. The crude oil spot prices, oil future prices, natural gas spot, and natural gas future prices were obtained from the Energy Information Administration (EIA). The crude oil prices were measured in dollars per barrel, while the natural gas prices were measured in dollars per million British Thermal Units (BTUs). The fertilizer prices were obtained from the World Bank Global Economic Monitor Database and were measured in dollars per metric ton. The potash and nitrogen market data were obtained from the U.S. Department of Agriculture (USDA) National Agricultural Statistics Service (NASS). Both the ARDL model and the GARCH model were used to evaluate the effects of oil, natural gas, and fertilizer prices, and to model the volatility in global fertilizer, oil, and natural gas prices.

2.4 Research Design

Our research design is as follows: In the first stage, we conduct an ARCH Lagrangian multiplier (LM) test to determine the volatility in fertilizer prices. In the second stage, using a Schwartz-Bayes information criterion (BIC), we determine the best model fit. In the final phase, we conduct a post-estimation analysis to validate our GARCH model.

3. Results

In this section, we first provide a few descriptive statistics and graphical analysis to highlight the volatility in oil, natural gas and various fertilizer prices. This is followed by the mean and volatility models of various fertilizer prices using appropriate ARMA-GARCH models. Finally, we validate our model using the null hypothesis of no ARCH-effects in our post-estimation analysis.

3.1 Descriptive Statistics

Table 1. Descriptive statistics of fertilizer prices (Dollars per metric ton): December 1993 to August 2012

Statistics	TS_t	$Urea_t$	PC_t	DAP_t	RP_t
Mean	249.7	198.35	211.16	299.98	76.61
Median	175.31	171	122.5	210.81	43
Maximum	1131.5	770	872.5	1200.63	430
Minimum	122.5	63	103.5	135	33
Std. Deviation	195.17	126.66	172.58	215.96	80.19
Skewness	2.73	1.82	2.08	2.43	2.72
Kurtosis	10.82	7.44	6.73	9.22	10.28
Jarque Bera	826.53	299.68	284.54	567.84	750.94
N	218	218	218	218	218

Source: Computed by the authors.

Table 1 shows the descriptive statistics for various fertilizer prices: Triple superphosphate (TS), urea, potassium chloride (PC), diammonium phosphate (DAP), and rock phosphate (RP), covering the full sample period. There is significant variation in fertilizer prices over the entire sample period as shown by the huge differences between the minimum and maximum values.

Table 2. Correlations of fertilizer prices: December 1993 to August 2012

	TS_t	$Urea_t$	PC_t	DAP_t	RP_t
TS_t		0.81	0.77	0.001	0.91
$Urea_t$	0.81		0.71	0.15	0.69
PC_t	0.77	0.71		-0.17	0.89
DAP_t	0.001	0.15	-0.17		-0.15
RP_t	0.91	0.69	0.89	-0.15	

The correlation coefficient from Table 2 suggests that triple superphosphate (TS) prices are highly correlated with urea, potassium chloride (PC), and rock phosphate (RP) prices. Urea prices are also highly correlated with potassium chloride prices, while potassium chloride prices are highly correlated with rock phosphate prices. Diammonium phosphate (DAP) prices are not correlated with any other fertilizer prices, while rock phosphate prices are highly correlated with TS, urea, and PC prices.

3.3 Graphical Analysis of Fertilizer Price Volatility

In this section, we provide a graphical analysis of oil prices, natural gas prices and fertilizer price volatility for our sample period.

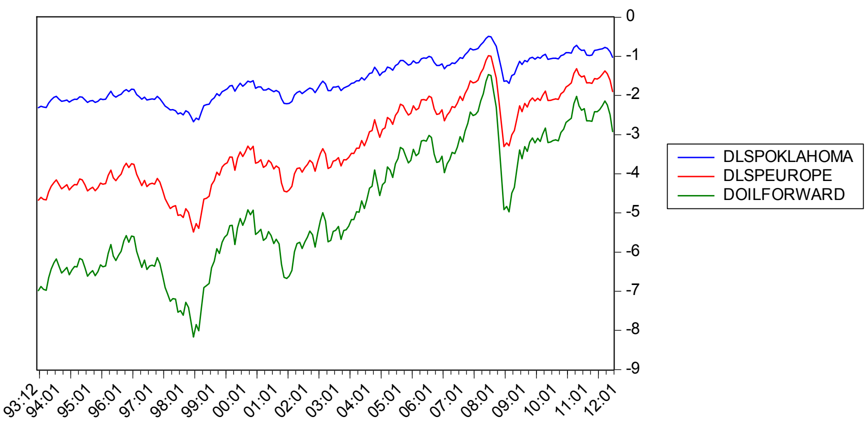

Figure 1. Trend of Real Prices of Crude Oil Spot prices in Oklahoma, Europe and Crude Oil Futures-December 1993 to January 2012

As evident from Figure 1, the correlations between spot oil prices based in Oklahoma, spot oil prices based in Europe and forward prices of oil are highly correlated during the sample period with the correlation coefficient being 0.995 between spot oil prices based in Oklahoma and spot oil prices based in Europe. This may be because the transmission of information in these markets is instantaneous in this market.

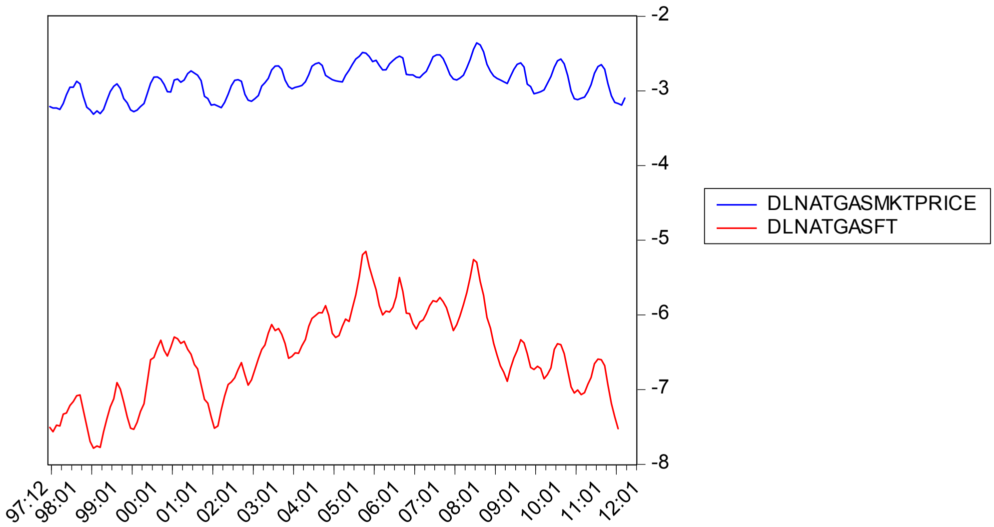

Figure 2. Trend of Real Natural Gas Spot and Future Prices-January 1997 to January 2012

Figure 2 shows the correlations between natural gas market prices and forward prices of natural gas. The correlation coefficient between these two indicators is also quite – 0.77.

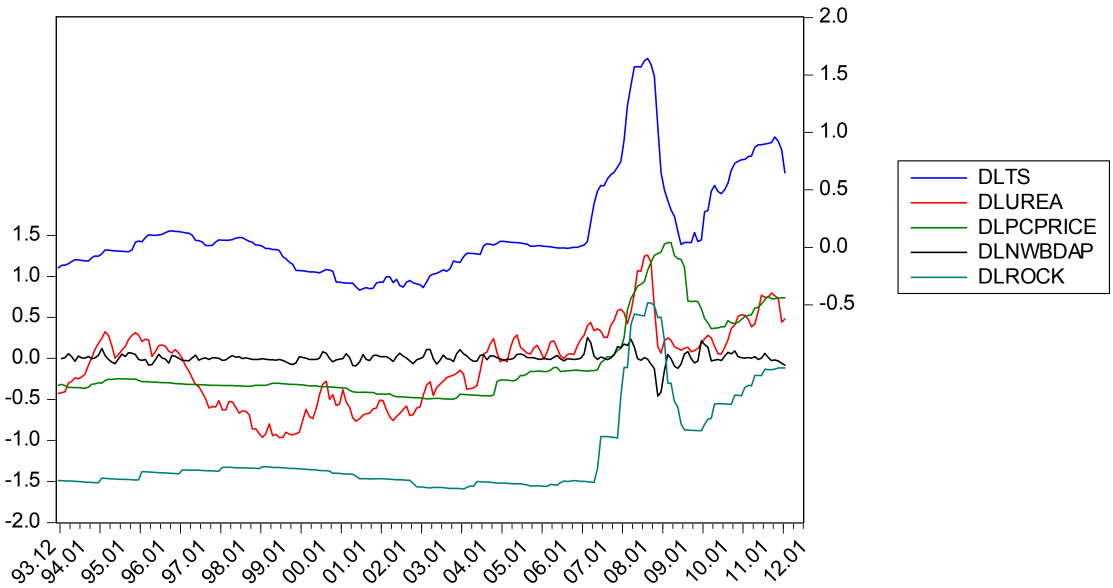

Figure 3. Trend of all Fertilizer Prices-December 1993 to January 2012

Figure 3 shows the price variation of all the fertilizer prices. As evident from this graph, all the fertilizer prices exhibited significant volatility during the crisis period- June 2007 to June 2008, which had implications for agricultural markets.

3.3 Statistics and Data Analysis: Pre-Estimation

The purpose of this section is to determine whether there is presence of ARCH effects in the fertilizer price series. This will then be consistent with large volatility in fertilizer prices over the sample period. Equation (14) specified the models of determining fertilizer prices, where FP stands for fertilizer price.

$$FP_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i FP_{t-i} + u_t \ ; \ i = 1, 2, \ldots \ldots, p; \ t = 1, \ldots . T; u_t \sim IID(0, \sigma^2); |\alpha_i| < 1 \quad (14)$$

Based on Engle's approach, an ARCH- LM test can be performed in two steps: first, estimate equation (14) by OLS and obtain the fitted residuals and second, regress the square of the fitted residuals on a constant and lags of the squared residuals. For example, estimate equation (14) as:

$$\widehat{u_t^2} = \theta_0 + \theta_1 \widehat{u_{t-1}^2} + \cdots \ldots \ldots . + \theta_p \widehat{u_{t-p}^2 +} \varepsilon_t \quad (15)$$

The LM test for the joint null hypothesis is given by: $H_0 : \theta_1 = \theta_2 = \cdots = \theta_p = 0$. In other words, there is no ARCH effect present in the model. The usual F-test or the test statistic computed by multiplying the number of observations (n) by the coefficient of determination (R^2) obtained from the regression equation of (15) is used. The latter test statistic $n\,R^2 \sim \chi_p^2$, where p is the degree of freedom that equals the number of autoregressive terms in equation (15).

Table 3. ARCH test – Dependent variable: fertilizer prices with different autoregressive parameters and lag length of the dependent variable

Mode	Variables	*p=1*		*p=5*		*p =10*	
		F-test	$n\,R^2$	*F-test*	$n\,R^2$	*F-test*	$n\,R^2$
k= 1	*TS*	40.68***	34.50***	8.20***	35.2***	1.98**	19.02**
	Urea	15.85***	14.89***	9.31***	39.09***	5.089***	42.67***
	PC	1.49	1.494	3.76***	17.73***	2.26**	21.44**
	DAP	51.92***	42.17***	10.55***	43.24***	8.02***	60.11***
	RP	9.40***	9.09***	5.07***	23.25***	4.07***	35.65***
k =2	*TS*	3.97**	3.93**	2.12*	10.39*	2.41***	22.68***
	Urea	0.90	0.91	7.67***	33.24***	4.34***	37.51***
	PC	14.41***	13.62***	7.25***	31.71***	3.90***	34.35***
	DAP	2.93*	2.91*	2.71**	13.10**	3.40***	30.62***
	RP	2.91*	2.90*	4.81***	22.15***	3.26***	29.49***

Source: Computed by the authors.

Notes: Model follows the autoregressive process in equation (1) of order k =1 and 2 respectively and p denotes the lag length for the test statistics based on equation (2).

The asterisks ***, **, and * denote 1%, 5%, and 10% levels of significance respectively.

Table 3 shows the test-statistics for the existence of ARCH effects in the variables. All the fertilizer price series show evidence of ARCH effects as evidenced by the F-test and $n\,R^2$ up to 10 lags for the triple superphosphate series. All the test statistics are statistically significant at 1% and 5% respectively, thus rejecting the "no ARCH" hypothesis.

3.4 Sequential Bai-Perron Test Results for Structural Breaks

The sequential Bai-Perron multiple breakpoint tests were conducted for each of the fertilizer price series. The break-test options are given for a trimming value of 0.15 with the maximum number of breaks being 5. The results are reported in Table 4.

Table 4. Bai-Perron multiple breakpoint test for fertilizer price series based on *l+1* vs. *l* sequentially determined breaks

Fertilizer prices	Break tests	Scaled F-Statistic	Critical Value	Break Dates**
TS	0 vs 1*	101.37	8.58	1999 M09 and 2007 M05[a]
	1 vs 2*	199.15	10.13	
	2 vs 3*	73.41	11.14	
	3 vs 4*	57.09	11.83	
Urea	0 vs 1*	158.44	8.58	1997 M04 and 2006 M12[b]
	1 vs 2*	216.80	10.13	
	2 vs 3*	111.03	11.14	
	3 vs 4*	46.38	11.83	
PC	0 vs 1*	61.59	8.58	2005 M06
	1 vs 2*	71.25	10.13	
DAP	0 vs 1*	132.52	8.58	1999 M07 and 2007 M03[c]
	1 vs 2*	206.59	10.13	
	2 vs 3*	90.9	11.14	
RP	0 vs 1*	30.22	8.58	2007 M12
	1 vs 2*	18.14	10.13	
	2 vs 3*	30.84	11.14	
	3 vs 4*	30.43	11.83	
	4 vs 5*	26.99	12.25	

Source: Computed by the authors.

Table 4, column 5 identifies the break dates for each of the fertilizer price series. Most of these break dates correspond to the current fertilizer price volatility during the period June 2007 to June 2008. Additional break dates were also identified for each of the series but are not reported because the Bai-Perron multiple breakpoint tests the null of constant parameters against the alternative of two (unknown) breaks. If these breakpoints are denotes as $(\widehat{T_1}, \widehat{T_2})$, the Wald test for non-constancy of the parameters can be constructed. The least squares estimates $(\widehat{T_1}, \widehat{T_2})$ jointly minimize the sum squared errors. For 2 breaks, these estimates require $O(n^2)$ regressions which are cumbersome but feasible. On the other hand, for 3 breaks, these estimates require $O(n^3)$ regressions, which are not feasible. Thus, the two breakpoints of the null of constant parameters is used against the alternative of two unknown breaks.

3.5 Main Results

The empirical estimates for the alternative volatility models for the four fertilizer price series are given in Tables 5 through 8 for different time periods based on the structural break tests. Suitable models for triple superphosphate prices are ARMA(1,1) and GARCH (2,2) with threshold effects present for the entire sample period. For the period 2007 month six to 2012 month one, the appropriate model is ARMA(1,0) and GJR(1,1) (Note 5). The short-run persistence of shocks in the two periods are 0.469 and 0.934 respectively, while the long-run persistence of shocks are 0.899 and 0.954 respectively. These empirical outcomes suggest that the mean increase in triple superphosphate prices during the period 2007 month six to 2012 month one may be attributed to higher mean prices of crude oil and natural gas prices. Thus, from a policy perspective, it is important to understand the linkages between mean and volatility in energy prices and mean and volatility in fertilizer prices.

Table 5. Mean and volatility in triple superphosphate prices for Entire Sample Period (1993-2012) and for various Sub-Samples

Period	1993 M12 to 2012 M01	2007 M06 to 2012 M01
Series	ARMA(1,1)	ARMA(1,0)
(TS)	GARCH (2, 2) [a,b] with threshold effects present	GJR (1,1)
α_0	3.32***	2.27***
	(0.28)	(0.856)
Log Oil spot price (-1)	0.13***	0.446***
	(0.05)	(0.16)
Log Oil Spot price (-2)	0.60***	0.302*
	(0.04)	(0.128)
Log of Natural Gas price (-1)	-0.29***	0.223**
	(0.07)	(0.105)
AR(1)	0.86***	0.881***
	(0.015)	(0.053)
MA (1)	0.47***	
	(0.06)	
β_0	.001**	0.004**
	(.0008)	(0.002)
β_1	0.146***	0.721**
	(0.054)	(0.287)
β_2	0.215	
	(0.14)	
γ_1	0.54	0.025
	(0.46)	(0.211)
γ_2	-0.11	
	(0.28)	
δ_1	.215	0.426
	(0.14)	(0.59)
Short-run persistence[a]	0.469	0.934
Long-run persistence[b]	0.899	0.954
Second order stationarity condition[c]	0.791	
BIC	-2.28	-1.26

The asterisks ***, ** and * denote significance at 1%, 5% and 10% respectively.

[a] In case of GARCH (2,2) with threshold effects present, short-run persistence is defined as ($\sum\beta_i + \delta_1/2$).

[b] In case of GARCH (2,2) with threshold effects present, long-run persistence is defined as ($\sum\beta_i + \sum\gamma_i + \delta_1/2$).

[c] The second order stationarity condition is given by $\sum\beta_i + \sum\gamma_i < 1$.

Oil prices are the spot prices based on Oklahoma spot prices.

Table 6. Mean and volatility in urea prices for Entire Sample Period (1993-2012) and for various Sub-Samples

Period	**1993 M12 to 2012 M01**	**1993 M12 to 1997 M04**	**1997 M05 to 2006 M11**	**2006 M12 to 2012 M01**
Series (TS)	ARMA(1,1) GJR(1,1)	ARMA(1, 1) GJR(1,1)	ARMA(1,1) GJR(1,1)	ARMA(1,1) GJR(1,1)
Mean Equation				
α_0	6.64*** (1.39)	4.78*** (0.79)	1.95*** (0.22)	2.77*** (0.81)
Log Oil spot price (-1)	-0.157** (0.07)	0.15 (0.12)	0.602*** (0.079)	0.53*** (0.16)
Log of Natural Gas price (-1)	0.043 (0.07)	-0.08 (0.12)	0.346** (0.138)	0.29* (0.15)
AR(1)	0.98*** (0.01)	0.86*** (0.05)	0.595*** (0.079)	0.66*** (0.09)
MA (1)	0.35*** (0.07)	0.66** (0.07)	0.452*** (0.059)	0.44*** (0.14)
Variance Equation				
β_0	0.0005** (0.0002)	0.002*** (7.39E-06)	0.007*** (2.56E-06)	0.0004 (0.0005)
β_1	0.20** (0.102)	-0.24 (0.16)	-0.036 (0.25)	0.19 (0.11)
β_2				
γ_1	0.89*** (0.05)	0.55*** (0.23)	0.358*** (0.134)	0.96*** (0.12)
γ_2				
δ_1	-0.25** (0.114)	0.34 (0.37)	-.093 (0.237)	-0.34*** (0.11)
Short-run persistence[a]	0.075	-0.07	-0.081	0.02
Long-run persistence[b]	0.965	0.48	0.277	0.98
BIC	-1.876	-2.09	-1.439	-1.033

In case of GJR (1, 1) model, short-run persistence is defined as (β_1+ $\delta_1/2$).

In case of GJR (1, 1) model, long-run persistence is defined as (β_1+γ_1+ $\delta_1/2$).

The asterisks ***, ** and * denote significance at 1%, 5% and 10% respectively.

The BIC criterion is used to determine the optimal lag length in the variance equation.

** There was significant presence of autocorrelation in the residuals for the 1993 month 12 to 2012 month one and we were unable to correct for this using first difference specification.

For the potassium chloride price series, no single model appropriately describes the mean and volatility of the prices. The second order stationarity conditions were also not satisfied for each time period and thus we do not report these results

Table 7. Mean and volatility in DAP prices for Entire Sample Period (1993-2012) and for various Sub-Samples

Period	**1993 M12 to 2012 M01**	**1993 M12 to 1999 M06**	**1999 M07 to 2007 M02**	**2007 M04 to 2012 M01**
Series (TS)	ARMA(1,1) GARCH(2,1)	ARMA (1,1) GARCH (2,1) with threshold effects present	ARMA(2, 2) GARCH (2,1)	ARMA(1,1) GARCH (2,1)
Mean Equation				
α_0	4.62*** (0.13)	5.33*** (0.21)	4.33*** (0.71)	2.31*** (0.65)
Log Oil spot price (-1)	0.144*** (0.02)	-0.06 (0.038)	0.076*** (0.019)	0.36*** (0.09)
Log Oil Spot price (-2)		0.09** (0.04)		0.334*** (0.04)
Log of Natural Gas price (-1)	0.211*** (0.05)	-0.05 (0.044)	0.104*** (0.039)	0.352*** (0.128)
AR(1)	0.96*** (0.01)	0.76*** (0.09)	0.599*** (0.177)	0.89*** (0.07)
AR (2)			0.379** (0.173)	
MA(1)	0.60*** (0.08)	0.47** (0.07)	1.38*** (0.13)	0.73*** (0.06)
MA (2)			0.559*** (0.102)	
Variance Equation				
β_0	0.002*** (9.45E-06)	0.002 (0.0004)	0.001*** (0.0003)	0.0007*** (2.36E-05)
β_1	0.09 (0.13)	-0.07 (0.06)	0.877** (0.463)	-0.08 (0.092)
β_2	-0.08* (0.05)	0.06 (0.069)	0.64* (0.35)	0.166* (0.09)
γ_1	0.36*** (0.125)	0.64 (0.54)	-0.871*** (0.067)	0.75*** (0.13)
γ_2				
δ_1		0.085 (0.22)		
Second order stationarity condition[c]	0.37	0.88	0.646	0.836
BIC	-2.823	-3.731	-3.773	-1.898

The asterisks ***, ** and * denote significance at 1%, 5% and 10% respectively.

[c] The second order stationarity condition is given by $\sum\beta_i + \sum\gamma_i < 1$.

The BIC criterion is used to determine the optimal lag length in the variance equation.

Table 8. Mean and volatility in rock phosphate prices for Entire Sample Period (1993-2012) and for various Sub-Samples

Period	**1993 M12 to 2012 M01**	**1993 M12 to 2007 M11**	**2007 M12 to 2012 M01**
Series (TS)	ARMA(2,2) GARCH(3,1)	ARMA(2,2) GARCH(3,1)	ARMA (1,1) GARCH (2,2) with presence of threshold effects
Mean Equation			
α_0	3.6*** (0.07)	3.55*** (0.112)	2.70*** (0.51)
Log Oil spot price (-1)	0.037*** (0.01)	0.044*** (0.017)	0.51*** (0.09)
Log of Natural Gas price (-1)	0.016 (0.02)	0.089*** (0.019)	0.126* (0.07)
AR(1)	0.87*** (0.03)	0.45 (1.17)	0.90*** (0.03)
AR (2)		0.50 (1.14)	
MA(1)	0.28*** (0.04)	0.82 (1.06)	-0.05 (0.05)
MA (2)		0.18 (0.26)	
Variance Equation			
β_0	0.0002*** (3.87E-05)	0.0004*** (2.03E-05)	7.53E-05 (0.0002)
β_1	0.39** (0.179)	0.46 (0.62)	0.01 (0.07)
β_2	0.05 (0.09)	0.05 (0.26)	0.52** (0.26)
β_3	0.04 (0.06)	-0.05 (0.04)	
β_4			
γ_1	-0.32 (0.23)	0.19 (0.27)	0.19 (0.13)
γ_2			0.21** (0.10)
γ_3			
γ_4			
δ_1			-0.04 (0.07)
Second order stationarity condition[c]	0.16	0.653	0.93
BIC	-5.25	-4.33	-1.03

The asterisks ***, ** and ** denote significance at 1%, 5% and 10% respectively.

[c] The second order stationarity condition is given by $\sum\beta_i + \sum\gamma_i < 1$.

The BIC criterion is used to determine the optimal lag length in the variance equation.

For the urea price series, an appropriate model is ARMA (1, 1) and GJR (1, 1) for the different time periods. The short-run persistence of shocks for the periods 1993 month twelve to 2012 month one, 1993 month twelve to 1997 month four, 1997 month five to 2006 month eleven, and 2006 month twelve to 2012 month one are respectively 0.075, -0.07, -0.08, and 0.02, while the long-run persistence of shocks are 0.965, 0.48, 0.28, and 0.98 respectively. These empirical estimates imply that short-run shocks do not persist, while the long-run shocks continue to persist. This may suggest that policy makers can look into the long-run relationship between oil price, natural gas price, and urea prices and find the equilibrium relationship between these prices. (Note 6)

For the DAP price series, the ARMA (1, 1) and GARCH (2, 1) describe the mean and volatility of the price series for the entire sample. Again, the second order stationarity conditions are satisfied for each period. It is interesting to note that the effects of lagged crude oil spot prices and natural gas prices is significant during the period 2007 month four to 2012 month one and has a much higher mean effect on DAP price series than other time periods. This again suggests higher and significant effects of the mean of crude oil prices and natural gas prices on DAP price series after the crisis period.

For the rock phosphate price series the ARMA (2, 2) and GARCH (3, 1) describe the mean and volatility equations appropriately. There is strong mean effects of lagged crude oil price and lagged natural gas prices on rock phosphate prices during the period 2007 month twelve to 2012 month one. The ARCH and GARCH effects are only significant during the period 2007 month twelve to 2012 month one.

Overall, the results suggest that appropriate volatility models for all the time periods can only be described for the urea and DAP price series, but not for other fertilizer price series. The results also suggest significant ARCH and GARCH effects for all the fertilizer prices during the period January 2007 to January 2012. This suggests that the lagged conditional variance and the squared error terms have significant effects on the conditional variance equation. Also the mean effects of lagged crude oil prices and lagged natural gas prices considerably have positive and significant impact on the fertilizer price series. This result corroborates with other studies that suggest higher and significant effects of the mean of crude oil prices and natural gas prices on DAP price series after the crisis period. (Note 7)

3.6 Post-Estimation and Validation

This study also conducted some post-estimation analyses to determine if the volatility models captured these effects. The post-estimation ARCH test is carried out using both the *F*-test and chi-square distributed $n R^2$ test. The results are presented in Table 9 and do not reject the null hypothesis of no ARCH effects. Most of the values are not statistically significant at the conventional level of significance. Thus, this study further validates the theoretical literature that ARCH/GARCH models are suitable for dealing with volatility in fertilizer prices.

4. Discussion

This paper examined the effects of crude oil price volatility and natural gas price volatility on fertilizer price volatility. This relationship is important as agriculture demands and supplies both energy inputs and energy outputs. To model the volatility in fertilizer prices, both symmetric models GARCH (1, 1) and asymmetric models GJR (1, 1) were considered. One interesting innovation of this study was to evaluate the effects of volatility over different time periods using Bai-Perron structural break tests. Results showed that the mean changes in oil prices and natural gas prices contributed to the increase in the mean of various fertilizer prices after the crisis period i.e. from June 2007 to June 2008. In addition, both the ARCH and GARCH effects were significant after the crisis period, suggesting that the volatility effects of oil and natural gas prices on fertilizer prices were also significant. The out-of-sample forecasts of the effect of higher energy prices on fertilizer prices were also considered. The results showed that, depending on the scenarios postulated, the maximum impact of higher energy prices fall on triple superphosphate and diammonium phosphate. The implication of this result is that higher production costs will add significantly to total expenditures for crop producers. These higher production costs, coupled with lower output prices, are likely to have a negative effect on farm profitability, thus reducing the investment levels in the farm sector.

Table 9. Post-estimation analysis of presence of ARCH effects of various fertilizer prices for the entire sample (1993-2012) and for various Sub-Samples

Fertilizer price	Period	*p=1*		*p=5*		*p =10*	
		F-test	$n\,R^2$	*F-test*	$n\,R^2$	*F-test*	$n\,R^2$
TS	1993 M12 to 2012 M01	0.048	0.048	0.33	1.70	2.49***	23.38***
	1993 M12 to 1999 M09	0.008	0.008	0.20	1.13	0.26	3.05
	1999 M10 to 2007 M05	0.172	0.176	0.171	0.909	0.14	1.59
	2007 M06 to 2012 M01	0.41	0.43	0.57	3.05	0.59	6.64
Urea	1993 M12 to 2012 M01	6.54**	6.40**	1.51	7.53	0.87	8.86
	1993 M12 to 1997 M04	0.34	0.36	0.46	2.61	0.59	7.22
	1997 M05 to 2006 M11	0.101	0.103	0.89	4.54	0.69	7.24
	2006 M12 to 2012 M01	1.52	1.53	0.88	4.53	1.40	13.28
PC	1993 M12 to 2012 M01	2.42	2.42	1.19	5.99	0.82	8.33
	1993 M12 to 1997 M04	0.081	0.085	0.58	3.23	0.54	6.72
	1997 M05 to 2006 M11	0.016	0.017	0.06	0.33	0.15	1.70
	2006 M12 to 2012 M01	0.31	0.32	0.22	1.21	0.38	4.47
DAP	1993 M12 to 2012 M01	0.07	0.07	1.16	5.80	3.38***	30.43***
	1993 M12 to 1999 M06	0.053	0.055	0.24	1.34	1.38	13.16
	1999 M07 to 2007 M02	2.58	2.57	1.11	5.62	1.09	10.96
	2007 M04 to 2012 M01	0.041	0.043	0.30	1.64	0.63	7.03
RP	1993 M12 to 2012 M01	0.002	0.002	0.05	0.28	3.46***	31.06***
	1993 M12 to 2007 M11	3.32*	3.21*	0.68	3.49	0.38	4.00
	2007 M12 to 2012 M01	1.16	1.18	0.43	2.39	0.81	8.73

Source: Computed by the authors (2015).

The asterisks ***, **, and * denote 1%, 5%, and 10% levels of significance respectively.

p denotes the lag length for the test statistics based on equation (15).

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Notes

Note 1. The GJR model is a GARCH variant that includes leverage terms for modeling asymmetric volatility clustering. In the GJR formulation, large negative changes are more likely to be clustered than positive changes. The GJR model is named for Glosten, Jagannathan, and Runkle (1993).

Note 2. The exponential GARCH (EGARCH) model is a GARCH variant that models the logarithm of the conditional variance process. In addition to modeling the logarithm, the EGARCH model has additional leverage terms to capture asymmetry in volatility clustering. The EGARCH(P,Q) model has P GARCH coefficients associated with lagged log variance terms, Q ARCH coefficients associated with the magnitude of lagged standardized innovations, and Q leverage coefficients associated with signed, lagged standardized innovations. We considered the EGARCH model as an additional specification in this study. However, this model did not perform well with respect to the BIC criterion. Thus, we do not report these results.

Note 3. All the variables in the above equation were converted to natural logarithms so that second-order moment conditions were satisfied.

Note 4. Bai and Perron (1998) show that for the test to have better power, $\widehat{\sigma^2}$ should also be consistent under the alternative hypothesis. The advantage of the above test is that it also allows the results to carry through for different distributions across segments for the regressors and the errors.

Note 5. We conducted regression models for the period 1993 month twelve to 1999 month nine and 1999 month ten to 2007 month five using ARMA(1,1) GJR(1,1) and ARMA(1,1) GARCH(2,2). As the residuals displayed significant autocorrelation owing to the short-sample size, we could not correct for this using first difference specifications. Thus, these results are not reported and may be obtained from the authors upon request.

Note 6. Determining the equilibrium relationship between energy and fertilizer prices and the substitution between crops and biofuels in a production function framework however is not trivial as it requires the formulation of full microeconomic model that depicts these relationships. Such an exercise is beyond the scope of this paper.

Note 7. For example, Chen et al. (2013) finds that the mean effect of oil price on global fertilizer prices was positive and significant after the crisis period. However, the authors did not incorporate the mean effects of natural gas prices on global fertilizer prices in their model.