Forecasting Volatility in Global Food Commodity Prices

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Abstract

To forecast volatility in global food commodity prices, in this paper a number of alternative competing models are employed, thin tailed normal distribution, and fat-tailed Student t-distribution GARCH models, beside a simple approach of forecasting volatility based on standard deviations over the previous months as a forecast of future volatility. Our results indicate the t-distribution model outperforms the other two approaches, whereas the simple standard deviation approach outperforms the normal distribution model, suggesting that the normality assumption of residuals which often taken for granted for its simplicity may lead to unreliable results of conditional volatility estimates. The paper also shows that some of the food commodity prices included in the study, such as wheat, rice, and beef exhibit long memory behavior, implying persistence of the effect of a shock for longer periods compared to other commodities in the group. The evidence of long memory process supports the view that structural changes in demand and supply side factors are more effective than short-term speculative factors.

تنبؤ التذبذبات في الأسعار العالمية للسلع الغذائية

ملخص

تهدف الورقة قياس دقة تنبؤات التذبذب للأسعار العالمية لمجموعة من السلع الغذائية باستخدام ثلاث نماذج إحصائية لقياس التذبذب المشروط لأسعار السلع. تتضمن النماذج الثلاث التوزيع الطبيعي الذي يتسم بذيل ضعيف، وتوزيع ت الذي يتسم بذيل سميك بالإضافة لاستخدام نموذج لا معلمية يستند للتذبذبات التاريخية. توضح نتائج الدراسة أن نموذج توزيع ت هو الأفضل من حيث دقة التنبؤ بالتذبذبات في الأسعار العالمية للسلع الغذائية موضع البحث وعليه ترجح الدراسة في عدم دقة التنبؤات في أسعار السلع الغذائية للعديد من الدراسات التطبيقية في هذا المجال إلى الاعتماد على نمذجة التذبذبات وفقاً لنموذج التوزيع الطبيعي.

1. Introduction

The soaring global food prices for the past three years exacerbated political and social unrest in many parts of the world, especially in those countries with high rates of unemployment and high poverty levels as manifested in recent public revolts, which toppled so far the ruling regimes in Tunisia and Egypt. The spillover effects of those uprises engulfed the whole Middle East region including Libya, Yemen, Bahrain, and Jordan. Political regimes, outside the Middle East, as in Africa, Asia, and Latin America, are also feeling the heat of the global food price volatility. All these countries included in their top agenda economic and distribution policies aiming to contain food price inflation in attempts to safeguard against potential political unrest. In Latin America countries, Honduras has frozen prices on a number of basic foodstuffs despite complaints from farmers. El Salvador government embraced a range of anti-poverty programs including food items subsidy policies, and Guatemala has slashed import tariff on wheat and considering programs of food and cash vouchers' handouts to poor peasants.

On supply side of food commodities catastrophic storms and droughts aggravated food production and storage capacities as flooding, powerful winter storms, massive cyclone and fire, destroyed in recent months large parts of farms in the major production sources including Australia, Russia and the United States of America. Beside disruptive demand and supply side factors analysts also attribute the rising volatility in food commodity prices to speculations in future commodity markets (FAO, 2008). However, Jeffrey Frankel (2008) attributes the soaring prices in food commodities to structural change in global demand for food items, mainly due to the high and rapid economic growth in countries like China and India. Whatever would be the prime cause behind the soaring food commodity prices, it is important to point out that volatility modeling 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 investigated volatility in food commodity markets from the perspective of spillover effect of crude oil price (Babula and Somwaru, 1992; Uri, 1996; Du et al., 2009; Onour, 2010). Broadly speaking, the literature on volatility forecast in commodity markets includes, two main approaches, implied volatility models which are based on option pricing formulas, and conditional volatility models of time series analysis.

However, it should be noted that the implied volatility approach of expected volatility has a number of draw backs. Among which as noted by Kroner et al. (1993), volatility forecast based on implied volatility approach may be more appropriate for short-term forecast, but may not yield reliable long-term forecast since usually trading is thin in options that are far away from their maturity dates.

As a result, in this paper we adopt time series modeling approach in forecasting conditional volatility in food commodity prices.

It is well documented (Bollerslev et al., 2003) that fat-tailedness in asset and commodity markets is intimately related to so-called volatility clustering, which describes the phenomena that large changes in prices, in either sign, tend to be followed by large changes, and small changes followed by small changes, reflecting market irregularities. Thus, volatility modeling can reveal market imperfection in global food commodity markets. Bollerslev et al. (2003) indicated that, the normality assumption is at odds when price changes exhibit fat-tailedness (leptokurtosis behavior). It has been evidenced recently by a number of authors (Brooks and Persand (2003), Vilasus (2002), and Hansen and Launda (2003), the standard GARCH models which use normality assumption has inferior forecasting performance compared to models that reflect skewness and kurtosis in innovations. In this paper beside the normal distribution based GARCH approach, we employed t-distribution based GARCH model, and simple historical volatility approach, based on the sample standard deviation returns over the previous months as a forecast of future volatility. We will refer to this approach the simple historical approach. This approach is included in our study because Bartunek and Mustafa (1991) find that for stock markets the simple historical approach outperformed more sophisticated time series models. This paper extends our previous work (Onour and Sergi, forthcoming), on volatility in food commodity prices in two respects. First, it extends the sample size of the data to include the latest global supply side disruptions of food commodities in 2009, and 2010. Second, the paper employs beside normal distribution and t-distribution specification of volatility a distribution free approach of forecasting volatility.

The paper is divided into four sections. Section two includes the methodology of the research. Section three deals with the estimation procedure and discussion of the results. In the final section we conclude the research findings.

2. Methodology

2.1 Volatility forecast

Given that p_t is the commodity price at time t, and I_{t-1} is the information set at time t-1, then the standard GARCH(1,1) model specified on normal distributed and Student t-distributed error terms defined as:

$$\ln\left(\frac{p_t}{p_{t-1}}\right) \equiv y_t = \mu + \varepsilon_t \qquad (1)$$

$$f(\varepsilon_t \setminus I_{t-1}) \sim N(0, \sigma_t^{\,2}) \qquad (2)$$

$or,$

$$f(\varepsilon_t \setminus \eta, I_{t-1}) \sim st(\eta; 0, \sigma^2{}_t) \qquad (2)'$$

where η is degrees of freedom, and

$$\sigma_t^{\,2} = w + \alpha\varepsilon^2{}_{t-1} + \beta\,\sigma^2{}_{t-1} \qquad (3)$$

Given an initial value for $\sigma_t^{\,2}$ (the conditional volatility) estimated values for $w, \alpha, and\ \beta$, in equation (3) can be used for estimating expected volatility at any given horizon time. Using equation (3), the expected volatility can be set (see Engle and Bollerslev, 1986, equation 22) as:

$$E(\sigma_{t+k}{}^{2} \setminus I_t) = \begin{cases} w + \alpha \varepsilon_t + \beta \sigma^2{}_t & if\ k = 1 \\ w + (\alpha + \beta) E(\sigma_{t+k-1} \setminus I_t) & if\ k \geq 2 \end{cases} \tag{4}$$

Alternatively, using recursive substitution of equation (3) we get,

$$E(\sigma_{t+k}{}^{2} \setminus I_t) = \begin{cases} w + \alpha \varepsilon_t + \beta \sigma^2{}_t & if\ k = 1 \\ w[1 + (\alpha + \beta) + \ldots.(\alpha + \beta)^{k-2}] + (\alpha + \beta)^{k-1}(w + \alpha \varepsilon_t + \beta \sigma^2{}_t) & if\ k \geq 2 \end{cases} \tag{5}$$

To test the predictive power of alternative competing models we employed the Root Mean Squared Error (RMSE), which is computed by comparing the forecast values F_{t+j} with the actually realized values, A_{t+j}, or $RMSE(k) = \sqrt{\sum_{j=0}^{N_k - 1} \frac{[F_{t+j+k} - A_{t+j+k}]^2}{N_k}}$

Where k=1,2,3 denotes the forecast horizon, N_k, is total number of k-steps ahead forecasts.

Equations (4) and (5) yield forecast of conditional volatility at horizons 1,2 …k.

It is well documented that the standard GARCH specification as stated in equations (2) and (3), fail to fully account for leptekurtosis of high frequency time series when assumed to follow normal distribution. Bollerslev et al. (2003) indicate ARCH models with conditional normal errors, result in a leptokurtic unconditional distribution. However, the degree of leptokurtosis induced by the time-varying conditional variance often does not capture all of the leptokurtosis present in high frequency speculative price data. To circumvent this problem Bollerslev et al. (2003) suggest use of Student t-distribution with degrees of freedom greater than two.

When the residual errors in (3) distributed Student t-distribution the density function in equation (3) can be specified as:

$$f(\varepsilon \setminus \eta) = \frac{\Gamma(\eta + 1)/2}{\sqrt{\eta \pi}\Gamma(\eta / 2)} \left(\frac{\eta}{\eta + \varepsilon^2} \right)^{(\eta+1)/2} \qquad for -\infty < \varepsilon < \infty \tag{6}$$

where $\Gamma(.)$, denotes gamma function, and η is the degrees of freedom.
Now, we have two competing models, (equations 2 and 6), for estimation of expected conditional volatility parameters in equation (5).

Given there is no common single conventional model selection criteria, to assess the goodness-of-fit for the two models we employed, the predictive power performance criteria, and three other criterias including the log-likelihood function, Akaike information criteria (AIC), and Schwarz criteria (SC) as indicated below:

$$AIC = -2(l/T) + 2(k/T)$$
$$SC = -2(l/T) + k \log(T)/T$$

Where k and (T) are respectively the number of parameters and the sample size, and l is the lag length. The model that minimizes the above information criteria considered the best fit, given that the model also yield highest log likelihood value and the best predictive power represented in the smallest Root Mean square Error (RMSE) values.

To capture volatility persistence we also need to address the ARFIMA process as indicated in the following section.

2.2 Volatility persistence

2.2.1 The ARFIMA(p,d,q) process

GARCH(p,q) models often used for modeling volatility persistence which have the features of relatively fast decaying persistence. However, in some cases volatility shows very long temporal dependence, i.e., the autocorrelation function decays very slowly. This motivates consideration of Fractionally Integrated Generalized Autoregressive Conditional Hetroskedasticity (FIGARCH) process:

$$\phi(L)(1-L)^d(y_t-\mu)=\theta(L)\varepsilon_t \tag{7}$$

where

$$\phi(L)=\sum_{j=1}^{p}\phi_j L^j \ , \quad \theta(L)=\sum_{j=1}^{q}\theta_j L^j ,$$

$$(1-L)^d=\sum_{j=0}^{\infty}\left(j^d\right)(-1)^j L^j=1-dL+\frac{d(d-1)L^2}{2}-.....$$

and L is lag operator, d is fractional differencing parameter, all roots of $\phi(L)$ and $\theta(L)$ assumed to lie out side the unit circle, and ε_t is white noise. The ARFIMA (p,d,q) in volatility can be defined(Baillie et al., 1996) as*:

$$\varphi(L)(1-L)^d\varepsilon_t^{\ 2}=w+\{1-\beta(L)\}v_t \tag{8}$$

where $\varphi(L)$ *and* $\beta(L)$ are respectively the AR(p) and MA(q) vector coefficients and $v_t=\varepsilon_t^{\ 2}-\sigma_t^{\ 2}$,

Following Baillie et al. (1996), Bollerslev and Mikkelsen (1996), Granger and Ding (1996), the parameters in the ARFIMA(p,d,q) and FIGARCH(p,d,q) models in (7) and (8) estimated using quasi-maximum likelihood (QMLE) method. In the ARFIMA models, the short-run behavior of the data series is represented by the conventional ARMA parameters, while the long-run dependence can be captured by the fractional differencing parameter, d. A similar result also applies when modeling conditional variance, as in equation (8). While for the covariance stationary GARCH(p,q) model a shock to the forecast of the future conditional variance dies out at an exponential rate, for the FIGARCH(p,d,q) model the effect of a shock to the

* For the FIGARCH(p,d,q) model to be well defined, and the conditional variance positive for all t, all the coefficients in the ARCH representation must be non-negative.

future conditional variance decay at low hyperbolic rate. As a result, the fractional differencing parameter, d, in the equations (7) and (8) can be regarded the decay rate of a shock to the conditional variance (Bollerslev, 1996).

In general, allowing for values of d in the range between zero and unity (or, 0<d<1) add a flexibility that play an important role in modeling long-run dependence in time series[†].

Bollerslev, 1996, indicates that if d=0, the series is covariance stationary and possess short memory process, whereas in the case of d=1 the series is non-stationary. However, in the case of 0<d<0.5, the series even though covariance stationary, its auto-covariance decays much more slowly than ARMA process. If d is 0.5<d<1 the series is no longer covariance stationary, but still mean reverting with the effect of a shock persist for a long period of time, and in that case the process is said to have a long memory. Given a discrete time series, y_t, with autocorrelation function, ρ_j, at lag j, Mcleod and Hipel (1978) define long memory as a process:

$$\sum_{j=-n}^{n}\left|\rho_j\right| \qquad as \quad n \to \infty \tag{9}$$

characterized as nonfinite. In the non-stationary and in the long memory process a shock at time t, continues to influence future y_{t+k} for a longer horizon, k, than would be the case for the standard stationary ARMA process. While there are varieties of ways to estimate the parameters of (3) and (4), in this paper we employed the maximum likelihood estimator.

To further check volatility persistence we need to investigate independent and identical distribution of price changes, using correlation integral approach as illustrated in the following section.

2.3 Correlation Integral

Since our primary goal in this paper to investigate the predictive power of alternative competing models, it remains to clarify predictability of future price changes based on the past changes. To do so, we need to test if our sample series exhibit independent and identical distribution behavior. Brock et al.,(1987) proposed a test (known as BDS test) of independent, identical distribution based on the correlation integral, a concept that arises in chaos theory. Kocenda (2001) proposed a modified version of BDS test that accommodates some of the shortcomings in BDS test. To explain Kocenda (2001) approach, let $Y_{t,n}$ be a part of a time series $Y_{T,T}=(Y_T,\ldots Y_1)$ such that $Y_{tn,}=(Y_t,Y_{t-1},\ldots Y_{t-n+1})$. Compare a pair of such vectors $Y_{tn,}$ and $Y_{sn,}$. The correlation integral is defined as:

$$C_{n,T}(\varepsilon) = 2(T_n(T_n-1))^{-1}\sum_{t=1}^{T_{n-1}}\sum_{s=t+1}^{T_n} I_\varepsilon(Y_{t,n},Y_{s,n})$$

[†] See Diebold and Rudebuch (1989); Cunado et al (2005); and Granger and Ding (1996) for a detailed discussion about the importance of allowing for non-integer values of integration when modeling long-run dependence in the conditional mean of time series data.

$where\, T_n = T - n + 1$, and $I(Y_{t,n}, Y_{s,n})$ is an indicator function of the event

$$\left\| Y_{t,j} - Y_{s,j} \right\| = \max \left| Y_{t+i} - Y_{s+i} \right| \le \varepsilon \quad \mathrm{i} = 0,1,\ldots \mathrm{n}\text{-}1 \tag{10}$$

So that, (Y_t, Y_s) in equation (10) are said to be no more than ε distant a part.
Brock et al (1987) defined

$$S(n,\varepsilon) = \hat{C}_n(\varepsilon) - \left[\hat{C}_1(\varepsilon)\right]^n \tag{11}$$

Where m, and ε respectively denote the embedding dimension (or lags) and the proximity parameters, which both to be defined, ex ante, by the investigator. Under the hypothesis that $\{Y_t\}$ is an i.i.d. process, (11) has asymptotic normal distribution with zero mean and variance (Brock et al (1987)). Note-that (11) depends on n and ε which the investigator has to choose and that the size of the test is very sensitive to these two parameters. To resolve such a problem, Kocend (2001) introduced some changes to BDS test, in his test known as K2K test. This alternative approach is based on calculating the slope of the log of the correlation integral versus the log of the proximity parameter, ε over a range of values of the proximity parameter, ε. The slope parameter in K2K test defined as:

$$\beta_n = \frac{\sum_{\varepsilon}((\ln(\varepsilon) - \ln(\bar{\varepsilon}))(\ln(c_n(\varepsilon) - \ln(c_n(\bar{\varepsilon}))}{\sum_{\varepsilon}((\ln(\varepsilon) - \ln(\bar{\varepsilon}))^2} \tag{12}$$

where $\ln(\varepsilon)$ is defined as the log of proximity parameter, $\ln(c_n(\varepsilon))$ is the correlation integral value, and the variables with a bar stand for the mean values of the corresponding variables without a bar. Since a range of different values of m and ε in equation (12), the alternative modification of K2K testing procedure dispense with the pre-choice condition of the two parameter.

3. Empirical Results

Using monthly data of global food commodity prices for wheat, rice, sugar, groundnut, and beef this paper aims to compare the predictive power of alternative models. The time period of our sample covers from January 1981 to December 2010. The data collected from Index Mundi website, which extracted from the IMF, Primary Commodity Price Tables[‡]. Results in table (1) reject the null hypothesis of independent, identical distribution process for all commodity prices in the table. To estimate the parameters in equations (2) - (5) we used maximum likelihood estimation procedure. Price changes included in figures (1) to (5), reveal evidence of fat-tailedness of price changes as revealed by the frequent spikes of price changes, indicating evidence of volatility clustering, which is the phenomena that large changes in prices, in either sign, tend to be followed by large changes, and small changes followed by small changes. Table (2) presents estimation results of the parameters in the conditional volatility equations (2)-(3), under the normal and the t-distribution residual error terms. Results of GARCH(1,1) parameters show evidence of stationarity of conditional volatility. The log likelihood, and the information criteria test results overwhelmingly support the t-distribution specification of the innovations

[‡] http://www.indexmundi.com/

in the AR(1) model in equation (1). This is consistent with the existing literature on asset markets, which indicate evidences of conditional leptokurtosis in high and medium frequency data analysis (Bai et al., 2003). To further investigate, robustness of the t-distribution error terms specification we conducted, using in-sample forecast analysis, its predictive power compared to the normal distribution error terms and simple historical volatility approach, based on the standard deviation returns over the previous months as a forecast of future volatility, using Root Mean Squared Errors (RMSE) loss function criteria. Results in table (4) reveal the t-distribution model overwhelmingly outperforms the more popular normal distribution specification. Furthermore, the simple forecast approach based on historical standard deviations outperforms the normal distribution approach, indicating that the normality assumption despite its popularity in empirical research it may not yield reliable prediction of volatility in global food prices. Table (5) report FIGARCH(1,d,1) results, indicating evidence of stationary intermediate memory process (covariance stationary and slowly decaying auto-covariance) for sugar and groundnut. But the prices of beef, rice and wheat exhibit long memory behavior (covariance non-stationary, but mean reverting), indicating the likelihood of persistence of a shock for long periods. The evidence of long memory process support the view that volatility in those commodities is not driven by short-term speculative factors, but it is rather influenced mainly by structural changes in demand side factors, along the view point of Jeffrey Frankel (2008).

Table (1): K2K test

Embedding dimension	wheat	rice	sugar	beef	groundnut
m_2	0.63	0.52	0.82	0.83	1.05
m_3	0.70	0.58	0.94	0.95	1.28
m_4	0.76	0.65	1.06	1.08	1.51
m_5	0.83	0.71	1.17	1.19	1.73
M_6	0.90	0.77	1.28	1.30	1.95
m_7	0.96	0.82	1.40	1.40	2.18
m_8	1.03	0.88	1.52	1.51	2.39
m_9	1.09	0.94	1.64	1.62	2.60
m_{10}	1.15	1.00	1.75	1.73	2.80

Note: Epsilon range: 0.60 – 1.90.
Significance: all entries reject the null-hypothesis at 1%.

Table (2) : GARCH Parameters

	Wheat		Rice		Beef		Groundnut	
	Normal	**t-dist**	**Normal**	**t-dist**	**Normal**	**t-dist**	**Normal**	**t-dist**
w **(p-value)**	0.046* (0.00)	0.0025* (0.00)	0.037* (0.00)	0.002* (0.00)	0.035* (0.00)	0.0012* (0.00)	0.048* (0.00)	0.003* (0.00)
α **(p-value)**	0.41* (0.00)	0.022* (0.00)	0.45* (0.00)	0.026* (0.00)	-0.14 (0.23)	-0.005 (0.23)	-0.082 (0.56)	-0.005 (0.60)
β **(p-value)**	0.15* (0.00)	0.15* (0.00)	0.36* (0.00)	0.36* (0.00)	0.026 (0.61)	0.026 (0.62)	0.27* (0.00)	0.27* (0.00)
LLF	274	1310	204	1214	386	1566	75	1033
AIC	0.012	0.37E-4	0.018	0.64E-4	0.0067	0.89E-5	0.039	0.17E-3
SC	0.013	0.39E-4	0.019	0.66E-4	0.007	0.92E-5	0.040	0.18E-3

Note: Estimated values of parameters rounded into two decimals.
Terms in parenthesis are P-values.
*significant at 5% significance level.

Table (3) : GARCH parameters

	Sugar	
	Normal	**t-dist**
w **(p-value)**	0.075* (0.00)	0.006* (0.00)
α **(p-value)**	-0.038 (0.66)	-0.002 (0.76)
β **(p-value)**	0.138* (0.00)	0.14* (0.00)
LLF	197	1063
AIC	0.019	0.15E-3
SC	0.020	0.15E-3

Note: Estimated values of parameters rounded into two decimals.
Terms in parenthesis are P-values.
*significant at 5% significance level.

Table (4) - RMSE Loss functions

	RMSE Loss Functions		
	Normal	**t-dist.**	**Historical**
Wheat*			
A month	0.062	0.0034	0.036
2 month	0.074	0.0034	0.035
3 month	0.066	0.0032	0.038
Rice*			
A month	0.066	0.0038	0.036
2 month	0.088	0.0039	0.039
3 month	0.077	0.0036	0.042
Beef*			
A month	0.039	0.0014	0.025
2 month	0.037	0.0014	0.026
3 month	0.964	0.0014	0.025
Groundnut*			
A month	0.084	0.0057	0.040
2 month	0.086	0.0060	0.045
3 month	0.082	0.0056	0.042
Sugar*			
A month	0.088	0.0077	0.054
2 month	0.087	0.0078	0.059
3 month	0.084	0.0074	0.058

*The loss functions are based on h-month ahead forecast errors.

Table (5) - FIGARCH(1,d,1): t-distribution

parameters	**wheat**	**rice**	**beef**	**groundnut**	**sugar**
$\hat{d}_1$ (std.error)	0.47* (0.06)	0.56* (0.05)	0.55* (0.05)	0.41 (0.06)	0.45 (0.06)
$\hat{\phi}_1$ (std.error)	-0.24 (0.07)	-0.21 (0.07)	-0.48 (0.05)	-0.15 (0.07)	-0.16 (0.07)
$\hat{\theta}_1$ (std.error)	0.01 (0.98)	0.002 (0.95)	0.40 (0.99)	0.01 (1.0)	0.40 (0.97)
LLF	1288	1207	1546	1025	1035

*mean reverting, but long memory process.

4. Concluding remarks

To forecast volatility in global food commodity prices in this paper we employed thin tailed normal distribution, and fat-tailed Student t-distribution GARCH models, beside a simple approach of forecasting volatility based on standard deviations over the previous months as a forecast of future volatility. The sample period in the study covers monthly price series for food commodities of wheat, rice, beef, groundnut, and sugar, during the period from October 1982 to December 2010. Based on the predictive power of volatility forecast and other goodness of fit measures the analysis in the paper indicates the t-distribution model outperforms the other two approaches, revealing evidence of leptokurtosis in the volatility of food commodity prices. This result implies that if such leptokurtic behavior is not taken into account when estimating conditional volatility, the standard option pricing formula of Black and Scholes, which depends on expected volatility parameter, could lead into unreliable results when pricing future option contracts in commodity markets. Our results, also show evidence of stationary intermediate memory process (covariance stationary and slowly decaying auto-covariance) for sugar and groundnut. But the prices of beef, rice and wheat exhibit long memory behavior (covariance non-stationary, but mean reverting), indicating possible persistence of a shock for long periods. The evidence of long memory process support the view that, structural changes in demand and supply side are more influential than short-term speculative factors.

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Appendix

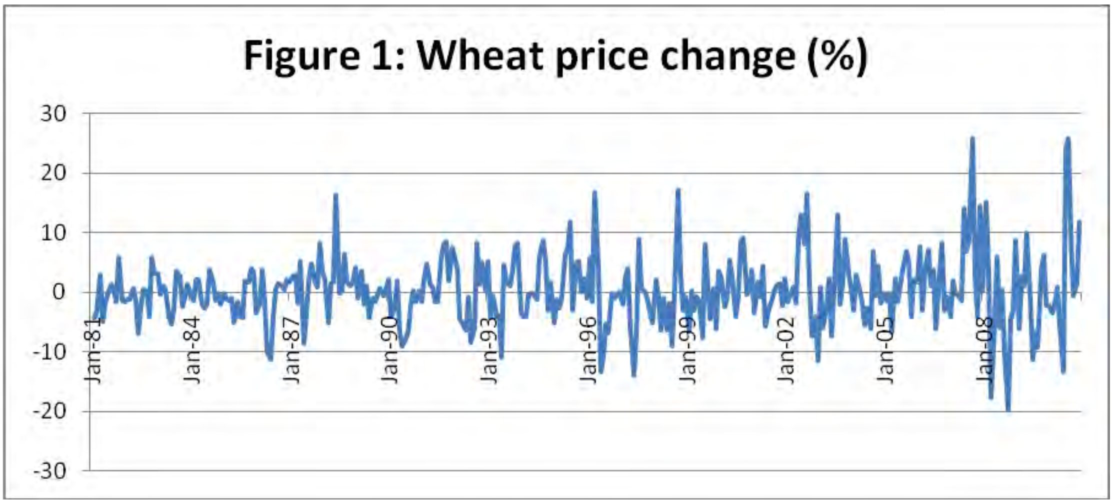
Figure 1: Wheat price change (%)
30
20
10
0
-10
-20
-30
Jan-81
Jan-84
Jan-87
Jan-90
Jan-93
Jan-96
Jan-99
Jan-02
Jan-05
Jan-08

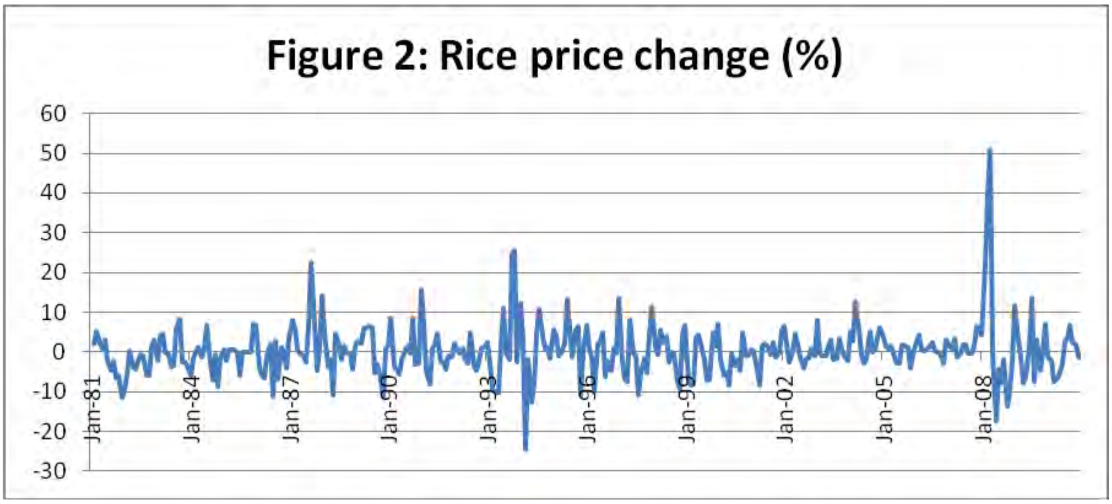
Figure 2: Rice price change (%)
60
50
40
30
20
10
0
-10
-20
-30
Jan-81
Jan-84
Jan-87
Jan-90
Jan-93
Jan-96
Jan-99
Jan-02
Jan-05
Jan-08

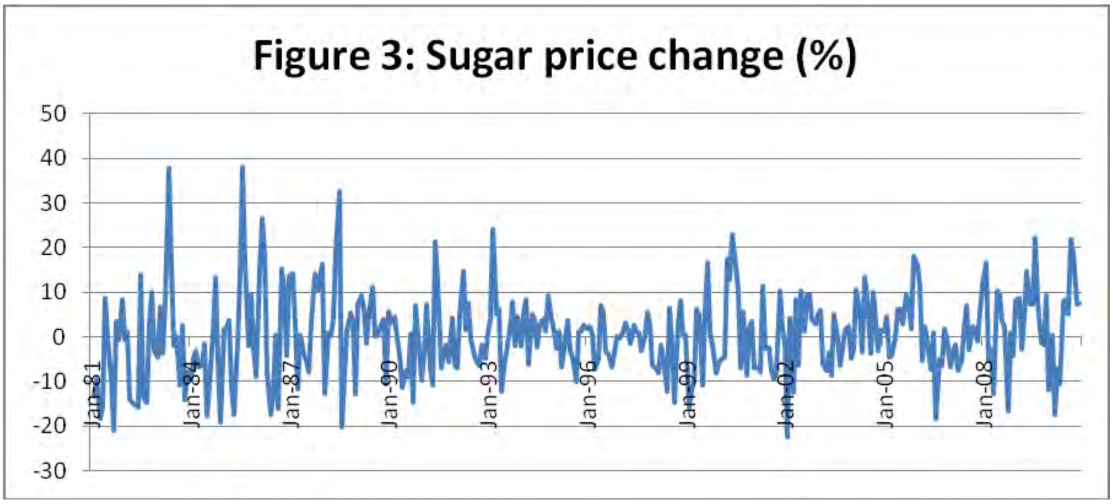
Figure 3: Sugar price change (%)
50
40
30
20
10
0
-10
-20
-30
Jan-81
Jan-84
Jan-87
Jan-90
Jan-93
Jan-96
Jan-99
Jan-02
Jan-05
Jan-08

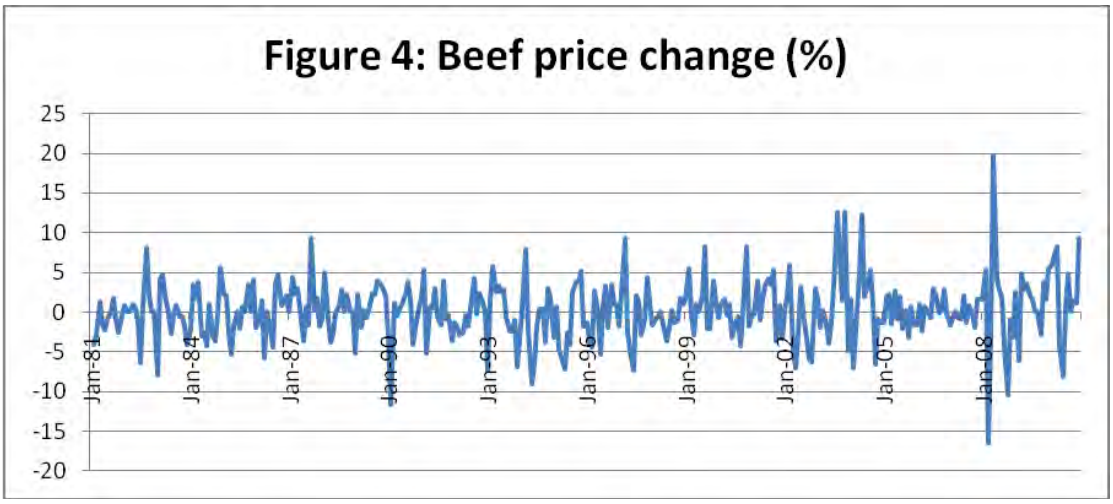
Figure 4: Beef price change (%)
25
20
15
10
5
0
-5
-10
-15
-20
Jan-81
Jan-84
Jan-87
Jan-90
Jan-93
Jan-96
Jan-99
Jan-02
Jan-05
Jan-08

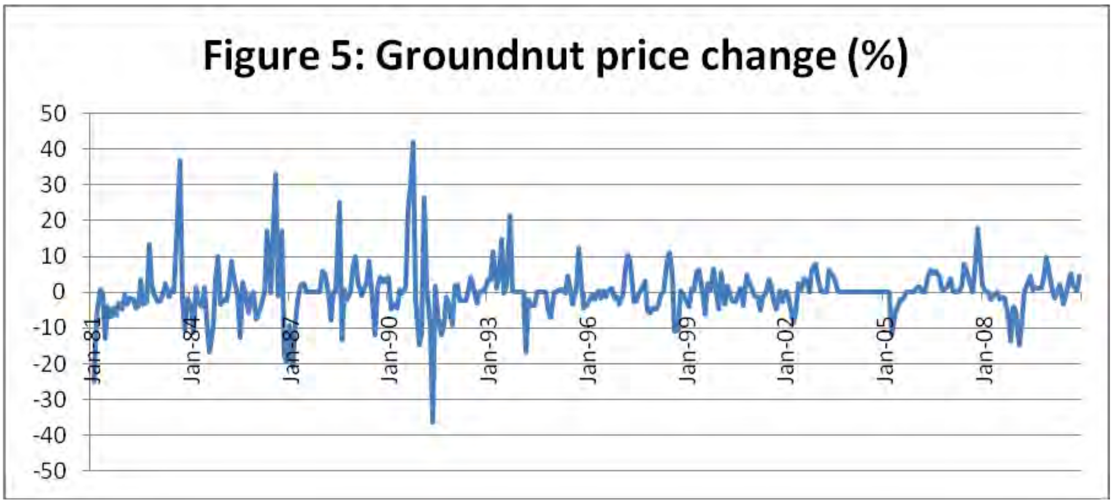
Figure 5: Groundnut price change (%)
50
40
30
20
10
0
-10
-20
-30
-40
-50
Jan-81
Jan-84
Jan-87
Jan-90
Jan-93
Jan-96
Jan-99
Jan-02
Jan-05
Jan-08

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