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Price Volatility in Agricultural Commodity Futures - An Application of GARCH Model*

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SUMMARY

Uncertain movement in commodity prices is a major concern for policy makers. Generalised autoregressive conditional heteroscedasticity (GARCH) model was applied to measure the extent of volatility in spot prices due to futures trading. The study sourced the available daily spot prices of selected twenty agricultural commodities that are traded in NCDEX platform both for 2009-10 (period of peak inflation) and right from the date of commencement of trading till June 2014. Empirical results indicated low price volatility in maize, soybean, cotton seed oilcake, castor, palm oil, cumin and chilli during the peak inflation period *i.e.*, 2009-10; whereas, chickpea, cotton seed oilcake, mustard and cumin experienced the same level of volatility right from inception of trading. The present study concludes that futures market helps to reduce price volatility but not necessarily in all the commodities. Hence, it is recommended that the commodity exchanges should continue the trading in commodities that exhibit low volatility. Further, actual economic reasons for the persistence of volatility in the rest of the commodities have to be probed.

Keywords: GARCH, Volatility, Futures trading, Agricultural commodity futures, NCDEX.

1. INTRODUCTION

Commodities have been the bedrock of civilization and have determined the fate and fortune of nations for eons and would continue to do so in future because of the volatility prevailing in their markets (Dasgupta and Chakrabarty 2009). Therefore, the price volatility drives the demand for hedging the risk in the commodity market.

Managing the price risk is considered to be one of the basic functions of futures market (FMC 2000). Trading in agricultural commodity futures market should stabilize their prices as a whole in the economy. But the issue over the past two decades was the rising food prices and they were more volatile than others (Chand 2010). Initially, in the mid 2007 futures was banned for certain commodities *viz.,* rice, wheat, pigeon pea and blackgram. The Indian Government again announced the ban on futures trading in four agricultural commodities namely chickpea, potato, rubber and soy oil on May 7, 2008. Subsequently in May, 2009 sugar was banned from trading. Listing, delisting and relisting the commodities on exchanges became a part and parcel of futures trading in the country, questioning the policy decision from all quarters.

The Abhijit Sen committee (2008) set up by the government to examine the impact of futures trading on food inflation reported that the cause and effect relationship between futures and spot prices cannot be

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established conclusively and the exact impact of futures trading on rising food prices is still under debate (Srinivasan 2008). Perhaps several researchers and institutions are still pondering on this debatable topic and most of the studies could not find any strong evidence of futures trading against the food inflation.

Generally, volatility in agricultural commodity prices originates mainly from the supply shocks. These disturbances coupled with the short-run demand and supply elasticity coefficients give rise to acute price fluctuations. Usually, commodity markets reveal that information flow on prices, hedging and speculation, and physical availability of commodities are the crucial factors that influence the volatility in prices. Increasing volatility in the prices of primary agricultural commodities has made speculation a common place in commodity markets. This feature can justify the use of informational based processes to model the pattern of price volatility (Vasisht and Bhardwaj 2010)

In an arbitrage free economy, price volatility is directly related to the flow of information. If futures market increases the flow of information utilizing the benefit of ICTs, then the spot commodity market exposes the degree of volatility from the futures market. The implication is that the volatility of asset price in market will rise due to the conditionality of increasing flow of information, thereby, generating the volatility in the spot market (Mahalik *et al.* 2009). Agricultural price data are inherently noisy, non-stationary and may be leptokurtic; hence it is difficult to capture the behaviour of prices. Even then, an attempt has been made in this study to analyse the price behaviour and estimate the volatility in spot market due to futures trading.

2. DATA AND METHODOLOGY

2.1 Data Source

National Commodity and Derivatives Exchange Limited (NCDEX), Mumbai was purposively selected for the present study as it holds a major share in agricultural commodities (47%) among other commodity exchanges operating in India. Top 20 commodities having the high monetary value in futures trade of NCDEX were selected purposively and historical time series data on spot prices (derived prices by a group of experts for the standardised commodity during trading days) were collected right from the date of commencement of trading till June 2014 as well as during 2009-10 considering the year as a peak for food price inflation.

2.2 Methodology

In general, any price series exhibit a tendency of volatility clustering *i.e.,* periods of high and low market uncertainty. Specifically, agricultural commodity prices require modeling within a flexible and unified framework. Despite several models exist to capture the volatility in price series, the vanilla Generalised Autoregressive Conditional Heteroscedasticity (GARCH) was used to measure the extent of volatility in agricultural commodity prices due to futures trading owing to its popularity and wide application by the economists and policy makers (Lee 1991). Bollerslev (1986) generalised the Engel's ARCH model which distinguishes not only between predictable and unpredictable components of prices but also allows the variance of unpredictable element to be time varying. Evidence of ARCH and GARCH is widespread in series that are partly driven by speculative forces. However, these may also be present in the behaviour of agricultural commodity prices with an expected positive transmission of volatility across commodities. Hence it takes the choice of widely used model in estimating the volatility in agricultural commodity prices.

Hitherto, the use of GARCH models in capturing the agricultural commodity price volatility has been limited in India unlike analysing the financial instruments. However, Mahalik *et al.* (2009), Vasisht and Bhardwaj (2010), Mahesha (2011), Sundaramoorthy *et al*. (2014) and a few others analysed the volatility in agricultural commodities.

The commonly used GARCH (1,1) model is defined below.

$$Y_{it} = a_0 + b_1 Y_{it-1} + b_2 Y_{it-2} + \varepsilon_{it} \qquad (2.1)$$

where, Y_{it} is the spot price of i^{th} commodity in t^{th} period and t is the time period ranging from 1, 2, 3… n. The variance of the random error is given as

$$\sigma_{i,t}^2 = \omega + \alpha_i \varepsilon_{i,t-i}^2 + \beta_i \sigma_{i,t-i}^2 \qquad (2.2)$$

The conditional variance equation specified in equation (2) is a function of three terms *viz.,* the mean (ω), news about volatility from the previous period measured as the lag of the squared residual from the mean equation (ε_{t-1}^2, the ARCH term) and the last period's forecast variance (σ_{t-1}^2, the GARCH term). The (1, 1) in GARCH (1, 1) refers to the presence of a first-order GARCH term (the first term in parentheses) and a first-order ARCH term (the second term in parentheses). The sum of ($\alpha_i + \beta_i$) gives the degree of persistence of volatility in the price series. Closer the sum to one, greater is the tendency of price volatility to persist for long time. If the sum exceeds one, it indicates an explosive time series with a tendency to meander away from mean value. The mean term (w) given in equation (2) is written as a function of exogenous variables with an error term. Since σ_t^2 is the one-period ahead forecast variance based on past information, it is called the conditional variance.

An ordinary ARCH model is a special case of a GARCH specification in which there are no lagged forecast variances in the conditional variance equation. Higher order GARCH models, denoted by GARCH (p, q), can be estimated by choosing either p or q or both greater than one. The representation of the GARCH (p, q) is given as,

$$\sigma_{i,t}^2 = \omega + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2$$

where, p is the order of the GARCH terms and q is the order of the ARCH term.

After fitting the model, it was tested for ARCH-LM (ARCH-Lagrange Multiplier test) to identify whether the fitted model has any further ARCH effect *i.e.,* testing white noise disturbances against GARCH disturbances in the linear regression model (Lee 1991). In plain term, ARCH-LM is the test for identifying the presence of serial correlation in the residuals of the fitted GARCH/ARCH series of models. The best fitted model with no further ARCH effects was presented and discussed further. EVIEWS 7 software has been used for estimating the GARCH/ARCH set of models.

3. EMPIRICAL RESULTS AND DISCUSSION

GARCH model was fitted to compute the extent of volatility in spot market prices consequent of futures trading in agricultural commodities. Daily historical prices, the best indicator of volatility are collected for representative spot market of selected commodities and transformed into natural logarithms. The analysis is done for two periods, *i.e.,* 2009-2010 and the whole period right from the starting date of futures trading till June 30, 2014 for a comparison. For the commodities which were suspended from trading irrespective of permanent or temporary during the study period, the particular price series block has been neglected and re-adjusted for capturing the real time volatility. Auto Regressive Integrated Moving Average (ARIMA) filtration analysis was first done to identify the best fit ARCH term and then proceeded with fitting the GARCH model.

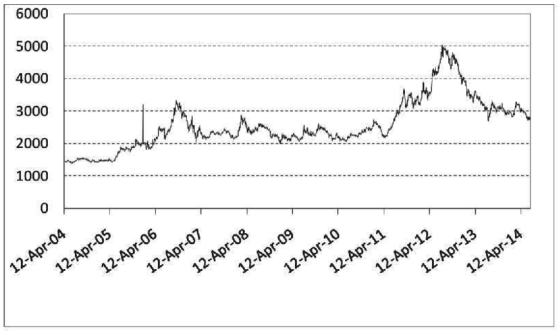
A visual analysis on behaviour of prices was done by plotting the daily spot prices of selected commodities (Fig. 1 to 4). Perusal of the charts indicates the temporary suspension of the selected commodities through a linear plot (absence of spot price data) in a block within the study period. Almost all the commodities showed an increasing trend owing to the rise in prices of agricultural commodities particularly rise in foodgrains prices questioned the integrity of the

Table 1. Estimates of fitted GARCH model for foodgrains and vegetables

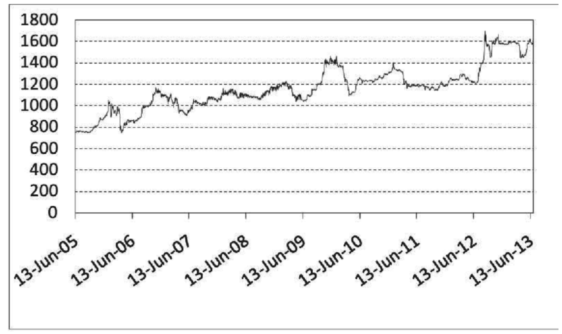
(2009-10)

Particulars	Chickpea	Wheat	Maize	Potato	Barley
Observations (days)	365	365	365	365	365
Standard deviation	126.75	117.55	35.90	396.09	73.08
Skewness	0.20	0.17	0.29	-0.36	0.49
Kurtosis	2.04	1.63	2.84	1.41	2.49
C.V (%)	5.52	9.41	3.93	38.53	7.89
GARCH estimates					
Constant	3.30E-06 (1.60)	6.95E-06** (5.83)	9.69E-06** (7.90)	0.0003 (1.52)	6.39E-06** (4.25)
Estimates of ARCH term (α_i)					
ε_{t-1}^2	0.0835** (3.65)	0.3294** (5.56)	0.2080** (7.06)	0.0033** (2.63)	0.1698** (4.77)
Estimates of GARCH term (β_i)					
σ_{t-1}^2	0.8885** (27.12)	0.2271** (3.10)	0.2882** (3.71)	0.8772** (10.86)	0.7579** (17.68)
σ_{t-2}^2	.....	0.4029** (4.86)	.....	.....	.....
Log likelihood	1139.41	1271.57	1477.69	624.98	1241.50
GARCH fit	1, 1	2, 1	1, 1	1, 1	1,1
$\alpha_i + \beta_i$	0.97	1.00	0.50	0.88	0.93
Volatility	Very high	Very high	Medium	High	Very high

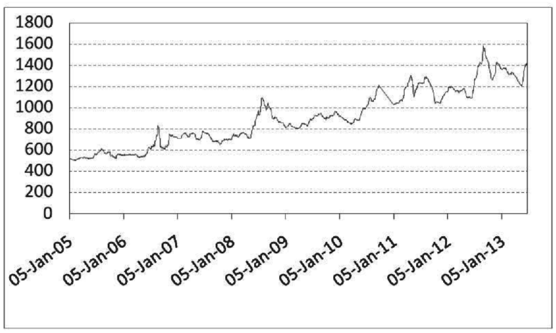
Note: Figures within parentheses indicate calculated z statistic, ** significant at 1 per cent level of probability (z statistic), * significant at 5 per cent level of probability (z statistic).



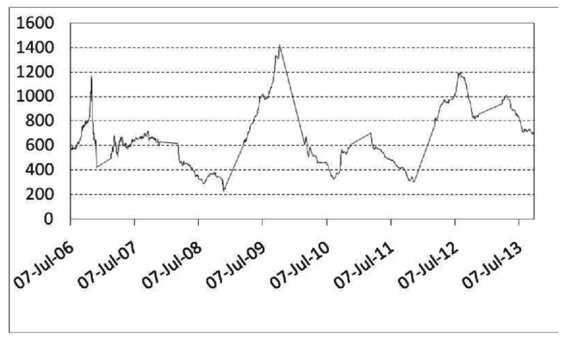
Chickpea-Delhi (₹/Quintal)



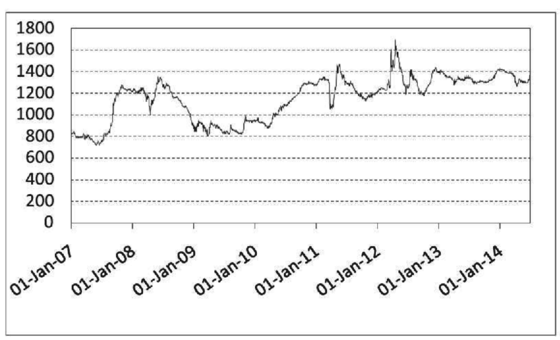
Wheat-Delhi (₹/Quintal)



Maize-Nizamabad (₹/Quintal)

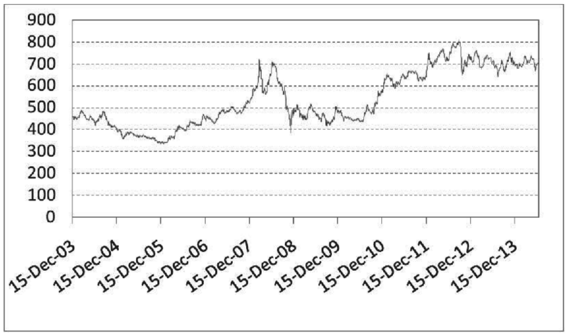


Potato-Agra (₹/Quintal)

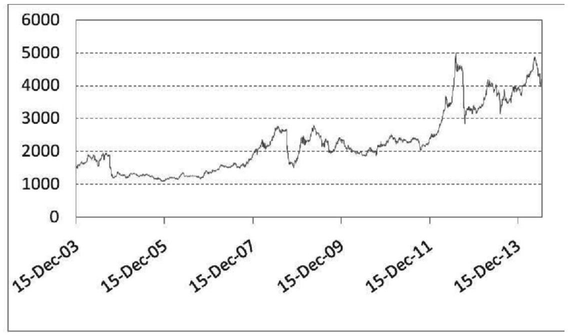


Barley-Jaipur (₹/Quintal)

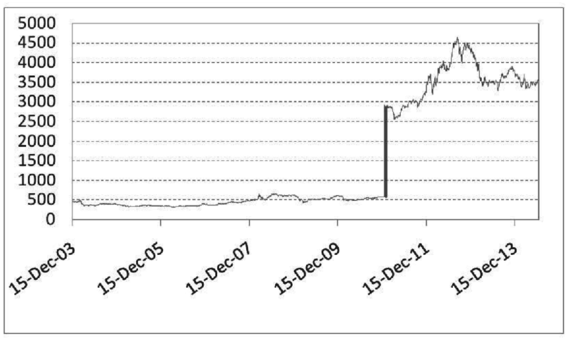
Fig. 1. Time series plot of spot prices for foodgrains and vegetables.



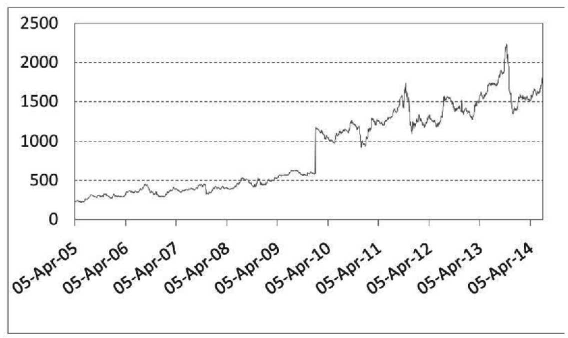
Soya oil-Indore (₹/10 kg)



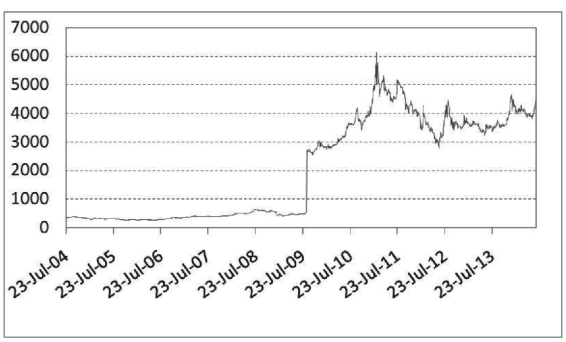
Soyabean-Indore (₹/Quintal)



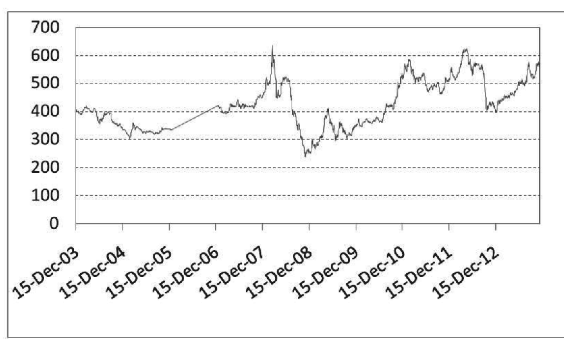
Mustard-Sri Ganganagar (₹/Quintal)



Cotton seed oil cake-Akola (₹/Quintal)

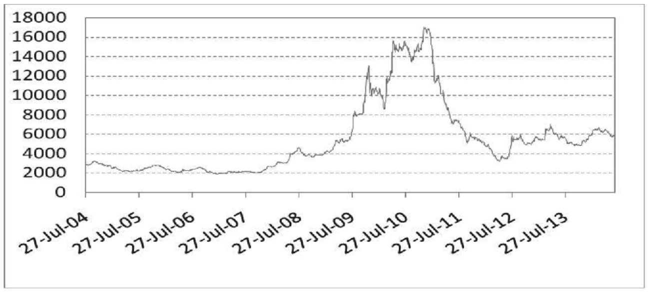


Castor-Disa (₹/Quintal)

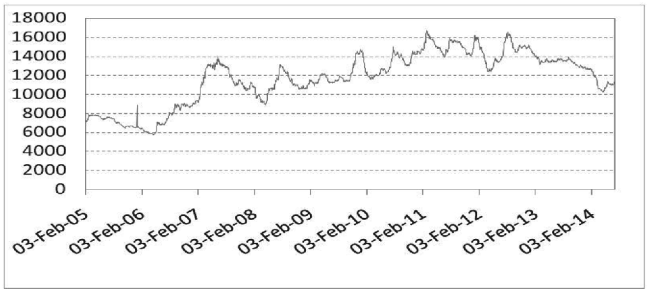


Palm oil-Kandla (₹/Quintal)

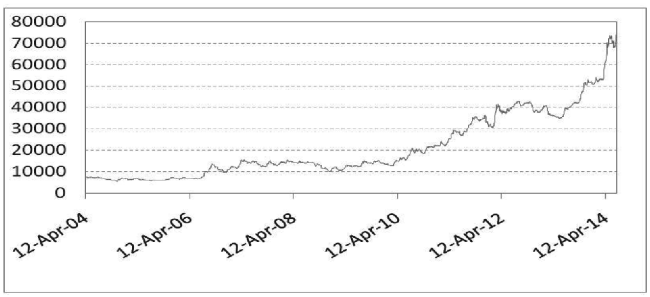
Fig. 2. Time series plot of spot prices for oilseeds.



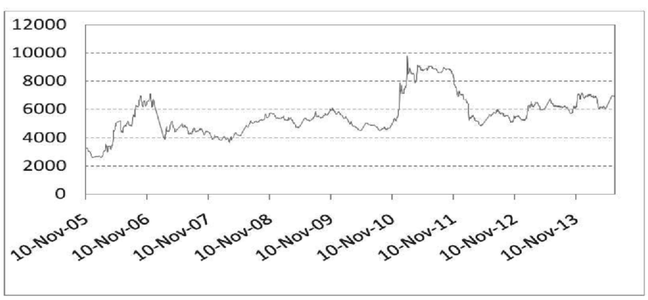
Turmeric-Nizamabad (₹/Quintal)



Cumin-Unjha (₹/Quintal)



Pepper-Kochi (₹/Quintal)



Chilli-Guntur (₹/Quintal)

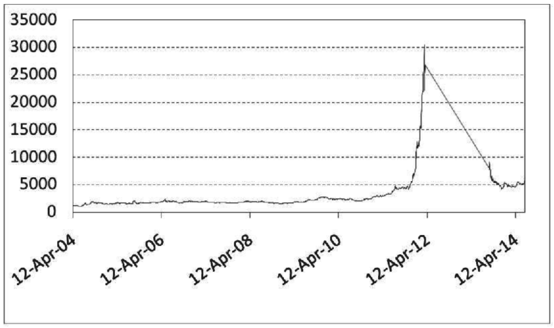
Fig. 3. Time series plot of spot prices for spices.

futures market. The increase in price is more prominent in maize, wheat, turmeric, guar seed and castor. Coefficient of variation was calculated for the 2009-10 price time series to know the instability in observations. The results indicated that the variation was more for potato (38.53%), followed by wheat (9.41%), barley (7.89%), chickpea (5.52%) and maize (3.93%) in the case of foodgrains and vegetables (Table 1). Castor exhibited more variation (34.59%) among the oilseed commodities (Table 2) followed by cotton seed oil cake (29.13%), soybean (7.33%) and crude palm oil (6.14%). Among spices (Table 3), turmeric experienced more variation in spot prices and in other commodities, sugar exhibited more variation (13.37%) followed by guar seed, guar gum, gur and kapas (Table 4). Variation in general was higher for the whole period compared to 2009-10. Potato experienced the highest variation (35.77%) among foodgrains and vegetables (Table 5). Mustard (109.74%), pepper (70.95%) and guar gum (111.88%) showed a maximum variation in spot prices respectively in oilseeds, spices and other commodities category.

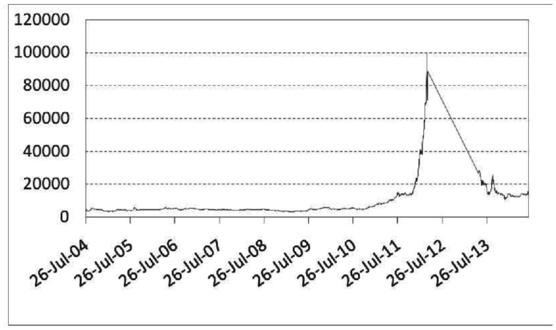
Table 1 to Table 8 presents the best fit GARCH models based on the log likelihood ratio criterion. The GARCH model results indicated that models of various order fit different commodities (Guida and Matringe 2004). Among the foodgrains and vegetables, highest GARCH order was found for wheat (2, 1) during 2009-2010 (Table 1). Rest of the commodities exhibited GARCH (1, 1). Excluding maize rest of the commodities exhibited high volatility in spot price. The results of the GARCH analysis clearly indicate that volatility in the current day depends on volatility in the preceding day for all the commodities as evident from the significant ARCH term.

Among oilseeds, soybean and castor were fitted only with the ARCH model (Table 2). The GARCH effect was observed for rest of oilseed commodities. Interestingly all the commodities exhibited GARCH (1, 1) indicating the current day volatility depends on the previous day price fluctuation. Oilseeds had some positive impact due to futures trading which is evident from the ($\alpha_i + \beta_i$) coefficients. Excluding refined soya oil and mustard, rest of the commodities exhibited low to medium volatility.

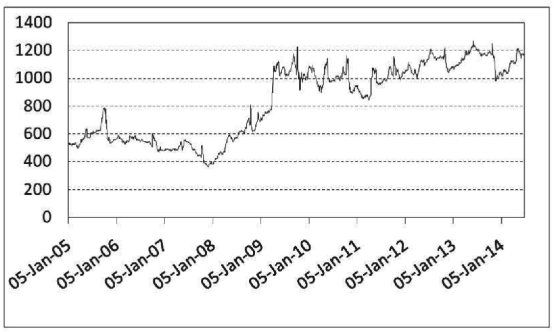
Turmeric and pepper spot prices indicated high volatility in price time series (Table 3). The ($\alpha_i + \beta_i$) coefficients showed that the volatility will persist for a longer time. On the contrary, cumin and chilli were fitted with ARCH (0, 1) model and clearly indicated low volatility. Current day volatility is influenced by the preceding day volatility in all the spice commodities selected for the present study.



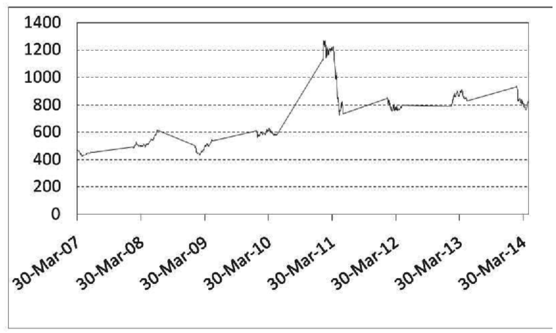
Guar seed-Jodhpur (₹/Quintal)



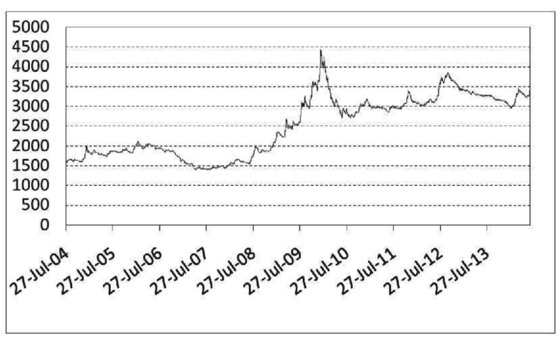
Guargum-Jodhpur (₹/Quintal)



Gur-Muzzafarnagar (₹/40 kg)



Kapas-Surendarnagar (₹/20 kg)



Sugar-Kolhapur (₹/Quintal)

Fig. 4. Time series plot of spot prices for other commodities.

All the commodities placed in the 'others' category showed high volatility in the price series and GARCH estimates indicated that the current volatility will persist for a longer time (Table 4). The volatility was extremely high in the case of gur ($\alpha_i + \beta_i = 1.83$) clearly indicating the 'explosive' nature of the price time series.

Table 2. Estimates of fitted GARCH model for oilseeds

(2009-10)

Particulars	Refined soya oil	Soybean	Mustard	Cotton seed oil	Castor cake	Crude palm oil
Observations (days)	365	365	365	365	365	365
Standard deviation	17.44	156.14	34.53	241.54	878.07	21.34
Skewness	0.70	0.28	0.98	0.09	–1.78	–0.56
Kurtosis	3.23	1.79	2.83	1.13	4.49	2.08
C.V. (%)	3.83	7.33	6.63	29.13	34.59	6.14
GARCH estimates						
Constant	5.92E-08 (0.38)	0.0001** (22.29)	5.45E-06 (1.56)	0.0009 (1.00)	0.0046** (25.22)	5.78E-05** (17.14)
Estimates of ARCH term (α_i)						
ε^2_{t-1}	0.0855** (5.41)	0.0538* (1.61)	0.0382** (2.63)	0.0045** (10.41)	0.0018* (2.17)	0.1752** (4.67)
Estimates of GARCH term (β_i)						
σ^2_{t-1}	0.9209** (75.57)	......	0.9086** (20.39)	0.5942* (2.47)	......	......
Log likelihood	1302.19	1146.13	1160.55	674.56	368.94	1232.80
GARCH fit	1, 1	0, 1	1, 1	1, 1	0, 1	0, 1
$\alpha_i + \beta_i$	1.00	0.05	0.95	0.60	0.00	0.17
Volatility	Very high	Low	Very high	Medium	Very low	Very low

Note: Figures within parentheses indicate calculated z statistic, ** significant at 1 per cent level of probability (z statistic), * significant at 5 per cent level of probability (z statistic).

Table 3. Estimates of fitted GARCH model for spices

(2009-10)

Particulars	Turmeric	Cumin	Pepper	Chilli
Observations (days)	365	365	365	365
Standard deviation	2667.25	953.02	1163.49	452.90
Skewness	0.20	1.12	0.31	-0.37
Kurtosis	2.33	3.18	2.65	2.07
C.V. (%)	25.48	7.71	8.01	8.50
GARCH estimates				
Constant	1.07E-05** (7.33)	4.51E-05** (34.44)	6.66E-06** (2.08)	4.70E-05** (94.71)
Estimates of ARCH term (α_i)				
ε^2_{t-1}	0.1790** (7.13)	0.0147** (3.40)	0.0443** (2.74)	0.0036** (3.19)
Estimates of GARCH term (β_i)				
σ^2_{t-1}	0.8499** (74.17)	....	0.8893** (19.90)	....
Log likelihood	937.99	1301.26	1174.09	1216.84
GARCH fit	1, 1	0, 1	1, 1	0, 1
$\alpha_i + \beta_i$	1.03	0.01	0.93	0.004
Volatility	Very high	Very low	Very high	Very low

Note: Figures within parentheses indicate calculated z statistic, ** significant at 1 per cent level of probability (z statistic), * significant at 5 per cent level of probability (z statistic).

Table 4. Estimates of fitted GARCH model for other commodities

(2009-10)

Particulars	Guar seed	Guar gum	Gur	Kapas	Sugar
Observations (days)	365	365	365	365	365
Standard deviation	218.76	442.65	63.06	28.93	450.75
Skewness	-0.13	-0.14	0.38	0.57	0.52
Kurtosis	2.85	3.55	3.27	1.79	2.63
C.V. (%)	9.38	8.85	6.12	5.16	13.77
GARCH estimates					
Constant	2.30E-05 (0.74)	1.67E-05* (2.29)	1.04E-05** (4.56)	3.46E-08** (5.99)	8.66E-06** (6.26)
Estimates of ARCH term (á$_i$)					
ε^2_{t-1}	0.0043* (1.58)	0.0457* (2.01)	1.4147** (15.55)	0.0039** (41.70)	0.0940** (2.73)
ε^2_{t-2}	....	....	....	....	0.2456** (4.90)
Estimates of GARCH term (â$_i$)					
σ^2_{t-1}	0.8097** (3.09)	0.8737* (17.37)	0.0458** (2.60)	1.0198** (952.08)	0.6636** (19.40)
σ^2_{t-2}	....	....	0.3719** (8.25)	....	....
Log likelihood	1123.06	1034.32	1088.65	1414.30	1164.17
GARCH fit	1, 1	1, 1	2, 1	1, 1	1, 2
$\alpha_i + \beta_i$	0.81	0.91	1.83	1.02	1.00
Volatility	High	Very high	Extreme high	Very high	Very high

Note: Figures within parentheses indicate calculated z statistic, ** `significant at 1 per cent level of probability (z statistic), * significant at 5 per cent level of probability (z statistic).

The results of the GARCH model for the whole period under consideration are furnished in Table 5 to 8. For foodgrain and vegetables, volatility in the current day depends on volatility in the preceding two days for wheat, and the previous day for the rest of the commodities (Table 5). The highest GARCH order was found for wheat (2, 1) and barley (2, 1). Excluding chick pea, the ($\alpha_i + \beta_i$) coefficients for rest of the commodities were more than 'one' indicating the persistence of volatility in spot prices of selected foodgrains and vegetables.

Table 5. Estimates of fitted GARCH model for foodgrains and vegetables

(from inception)

Particulars	Chickpea	Wheat	Maize	Potato	Barley
Observations (days)	8557	4411	3981	1624	4005
Standard deviation	758.47	205.22	266.02	236.48	204.66
Skewness	0.95	0.28	0.38	0.56	-0.49
Kurtosis	3.86	2.96	2.12	2.73	2.06
C.V. (%)	29.42	17.70	29.68	35.77	17.75
GARCH estimates					
Constant	5.12E-05** (11.73)	5.38E-07** (13.12)	3.16E-06** (24.97)	–5.52E-06** (-5.47)	1.44E-06** (7.28)
Estimates of ARCH term (α_i)					
ε^2_{t-1}	0.0223** (21.33)	0.0212** (6.93)	0.6860** (81.07)	2.5091** (67.30)	0.1403** (9.01)
ε^2_{t-2}	......	0.2205** (28.18)	......	......	0.1356** (5.40)
Estimates of GARCH term (β_i)					
σ^2_{t-1}	0.4032** (8.04)	0.3290** (11.35)	0.4737** (59.82)	0.5666** (106.19)	0.3296* (2.05)
σ^2_{t-2}	......	0.4660** (17.99)	......	......	0.4127* (3.07)
Log likelihood	28274.07	16727.67	15767.64	3603.968	14560.33
GARCH fit	1, 1	2, 2	1, 1	1, 1	2, 2
$\alpha_i + \beta_i$	0.43	1.04	1.16	3.08	1.02
Volatility	Low	Very high	Very high	Extreme high	Very high

Note: Figures within parentheses indicate calculated z statistic, ** significant at 1 per cent level of probability (z statistic), * significant at 5 per cent level of probability (z statistic).

Table 7. Estimates of fitted GARCH model for spices

(from inception)

Particulars	Turmeric	Cumin	Pepper	Chilli
Observations (days)	4344	4853	5493	3616
Standard deviation	3763.59	2753.57	14897.44	1425.68
Skewness	1.52	-0.53	1.17	0.55
Kurtosis	4.48	2.30	3.72	3.36
C.V. (%)	70.68	23.50	70.95	25.18
GARCH estimates				
Constant	1.51E-06** (24.62)	5.09E-05** (658.59)	3.79E-06** (17.92)	2.24E-05** (46.16)
Estimates of ARCH term (α_i)				
ε^2_{t-1}	0.00961** (31.90)	0.0618** (14.97)	0.1502** (14.68)	0.9132** (52.69)
ε^2_{t-2}	......	......	0.0387** (2.93)	......
Estimates of GARCH term (β_i)				
σ^2_{t-1}	0.9021** (418.58)	......	0.7472** (82.17)	0.5603** (80.16)
Log likelihood	14587.89	16970.43	19900.92	10918.5
GARCH fit	1, 1	0, 1	1, 2	1, 1
$\alpha_i + \beta_i$	1.00	0.06	0.94	1.47
Volatility	Very high	Very low	Very high	Extreme high

Note: Figures within parentheses indicate calculated z statistic, ** significant at 1 per cent level of probability (z statistic), * significant at 5 per cent level of probability (z statistic).

Table 6. Estimates of fitted GARCH model for oilseeds (from inception)

Particulars	Refined soya oil	Soybean	Mustard	Cotton seed oil cake	Castor seed oil	Crude palm oil
Observations (days)	8122	5676	6925	4948	4512	4803
Standard deviation	126.84	924.81	1391.04	513.03	1740.64	84.76
Skewness	0.38	0.91	1.15	0.38	0.25	0.24
Kurtosis	1.79	2.95	2.51	1.70	1.33	2.13
C.V. (%)	23.72	40.98	109.74	59.74	85.63	20.01
GARCH estimates						
Constant	3.06E-07** (18.09)	3.07E-06** (16.31)	0.0003** (1302.01)	0.0002** (690.36)	–1.12E-06** (–5.21)	7.60E-06** (14.65)
Estimates of ARCH term (α_i)						
ε^2_{t-1}	0.0889** (38.70)	0.2546** (81.94)	–0.0001** (–14.43)	0.0738** (12.36)	1.1067** (69.95)	0.0658** (12.61)
Estimates of GARCH term (β_i)						
σ^2_{t-1}	0.1416** (13.14)	0.7709** (152.05)	—	—	0.6987** (173.03)	0.8227** (67.79)
σ^2_{t-1}	0.7591** (71.35)	—	—	—	—	—
Log likelihood	33487.55	19832.87	16906.29	14368.86	13196.61	16814.15
GARCH fit	2, 1	1, 1	0, 1	0, 1	1, 1	1, 1
$\alpha_i + \beta_i$	0.99	1.03	-0.00	0.07	1.81	0.89
Volatility	Very high	Very high	Extreme low	Very low	Extreme high	High

Note: Figures within parentheses indicate calculated z statistic, ** significant at 1 per cent level of probability (z statistic), * significant at 5 per cent level of probability (z statistic).

Table 8. Estimates of fitted GARCH model for other commodities

(From Inception)

Particulars	Guar seed	Guar gum	Gur	Kapas	Sugar
Observations (days)	4808	4822	5076	1191	5376
Standard deviation	2675.10	8976.24	264.88	222.54	751.75
Skewness	5.45	5.00	-0.16	0.89	0.10
Kurtosis	40.42	35.80	1.40	2.99	1.60
C.V. (%)	98.86	111.88	31.76	32.42	30.23
GARCH estimates					
Constant	2.66E-06** (15.94)	3.95E-06** (9.06)	1.52E-05** (103.23)	3.43E-05** (20.29)	5.20E-07** (15.39)
Estimates of ARCH term (α_i)					
ε^2_{t-1}	0.0248** (4.13)	0.0509** (6.20)	0.2607** (42.43)	12.9074** (96.18)	0.1485** (28.47)
ε^2_{t-2}	0.1233** (18.70)	0.1749** (25.63)	1.5270** (134.19)	......	......
Estimates of GARCH term (β_i)					
σ^2_{t-1}	0.8611** (254.38)	0.1306** (3.19)	0.0897** (22.75)	......	0.7276** (14.31)
σ^2_{t-2}	......	0.4376** (7.28)	......	......	0.1180** (2.51)
σ^2_{t-3}	......	0.2188** (4.22)	......	......	......
Log likelihood	14633.77	14236.56	17917.87	3194.56	22003.7
GARCH fit	1, 2	3, 2	1, 2	0, 1	2, 1
$\alpha_i + \beta_i$	1.01	1.01	1.88	12.91	0.99
Volatility	Very high	Very high	Extreme high	Extreme high	Veryhigh

Note: Figures within parentheses indicate calculated z statistic, ** significant at 1 per cent level of probability (z statistic), * significant at 5 per cent level of probability (z statistic).

Excluding cotton seed oil cake and mustard, rest of the oilseeds showed very high volatility in spot prices for the whole period (Table 6) on contrary to 2009-10 (Table 2). Higher order GARCH (2, 1) model was fitted for refined soya oil indicating the influence of preceding day volatility on current day price fluctuation. However, a mixed response was observed in the case of spice economy against the report by Sen (2008). Pepper had a best fit of GARCH (1, 2) indicating the influence of preceding two days volatility on the current day price variation (Table 7). Price volatility in gur and kapas were extremely high indicating the 'explosive' nature of the price time series (Table 8) and rest of the commodities in 'others' category experienced a very high volatility.

Comparison of both the periods under study indicated only a miniscule change in the GARCH model ($\alpha_i + \beta_i$) coefficient. Barring a few commodities like chick pea, and, cumin, mustard and cottonseed oilcake which falls under ARCH category, the rest of the price series showed either an 'explosive' pattern or 'high' since the ($\alpha_i + \beta_i$) exceeds or closer to one, which infer the persistence of volatility in futures trading despite other factors influence the variation in price level. However, during mid-2009 the panic state reaction as a consequence of increase in the overall price of food commodities which blamed the operation of futures trading and resulted in delisting of sensitive commodities is partly supported by the study. In certain commodities like maize, soybean, cotton seed oilcake, castor, palm oil, cumin and chilli the futures market stablised the prices. The possible reason could be due to the professional management of the commodity exchanges and monitored by the market regulator from time to time.

4. CONCLUSIONS

Volatility represents an important risk factor of supply, especially in agricultural commodities. Agriculture being biological in nature and seasonal in production, prices fluctuates drastically than any other commodities. GARCH model was applied to capture the extent of volatility in spot prices due to futures trading. The results indicated that low volatility in price time series was observed in maize, soybean, cotton seed, castor, palm oil, cumin and chilli during the period of rising general price level which put the country in panic situation. Further, commodities like chick pea, cotton seed oilcake, cumin and mustard registered low volatility in spot prices right from the inception of futures trading. The present study concludes that futures trading could be a reason for reduction in price volatility but certainly not in all commodities. Agricultural price volatility is primarily caused by supply shocks. The extent of the volatility is determined by the variances of these shocks and by the elasticity coefficients of the supply and demand functions. Those who claim that price volatility will be higher over a long period must believe either that shock variances have increased or elasticity coefficients of demand and supply functions have declined. Despite these complexities, the study recommends that the commodity exchanges established both at national and regional level should continue the trading in commodities that has registered low volatility. For the rest of commodity prices which are highly volatile, the actual economic reasons for the persistence of volatility have to be probed and argued coherently.

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