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Modelling and Forecasting of Price Volatility: An Application of GARCH and EGARCH Models§

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Abstract

This paper has studied the autoregressive integrated moving-average (ARIMA) model, generalized autoregressive conditional heteroscedastic (GARCH) model and exponential GARCH (EGARCH) model along with their estimation procedures for modelling and forecasting of three price series, namely domestic and international edible oils price indices and the international cotton price 'Cotlook A' index. The Augmented Dickey-Fuller (ADF) and Philips Peron (PP) tests have been used for testing the stationarity of the series. Lagrange multiplier test has been applied to detect the presence of autoregressive conditional heteroscedastic (ARCH) effect. A comparative study of the above three models has been done in terms of root mean square error (RMSE) and relative mean absolute prediction error (RMAPE). The residuals of the fitted models have been used for diagnostic checking. The study has revealed that the EGARCH model outperformed the ARIMA and the GARCH models in forecasting the international cotton price series primarily due to its ability to capture asymmetric volatility pattern. The SAS software version 9.3 has been used for data analysis.

Key words: ARIMA, Cotlook A index, edible oils, EGARCH, GARCH, volatility, forecasting

JEL Classification: C 13, C 53, Q 13, Q 17

Introduction

Modelling and forecasting of prices of agricultural commodities is essential for policymakers as well as for various stakeholders in the marketing chain of these commodities, right from farmers to consumers. Most of the agricultural price series can be modelled as time-series data, where the information is collected over time at equal time-epochs. The Box Jenkins' autoregressive integrated moving average (ARIMA) methodology has dominated the arena of time-series forecasting for quite a long period, until the need of dealing with volatile data was felt. Interestingly, many agricultural commodities price data are inherently noisy in nature and are volatile too. This is because the agricultural commodity prices respond rapidly to the actual and the presumed changes in supply and demand conditions; and moreover, the weather-induced fluctuations in farm production worsen the situation. Sometimes, asymmetric phenomena also arise in price series, which tend to behave differently when economy moves into recession rather coming out of it. Many agricultural price series have shown periods of stability, followed by periods of instability with high volatility. So, to deal with such series, ARIMA model will not be enough, as it is restricted with assumptions of linearity and homoscedastic error variance.

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Volatility is the sudden unexpected rise or fall in the series which may upset the stakeholders. It is a well-established fact that the price volatility can destabilize farm income and restrict the farmers from making investments and using resources optimally (Schenepf, 1999). This can ultimately drive the much required resources away from the agricultural sector. The series is said to be volatile when a few error-terms are larger than the others and are responsible for the unique behaviour of the series, such a phenomenon is known as heteroscedasticity. To deal with heteroscedasticity, the popular and non-linear model is the autoregressive conditional heteroscedastic (ARCH) model, proposed by Engle (1982). The model was generalized by Bollerslev (1986) in the form of Generalized ARCH (GARCH) model for parsimonious representation of ARCH. In the GARCH model, the conditional variance is also a linear function of its own lags. As in ARCH, this model is also a weighted average of past squared residuals, but it has declining weights that never go completely to zero.

The GARCH models are widely used for modelling and forecasting of economic and financial series. Further, more advancement was made by using the AR specification with ARCH/GARCH models where it was found to forecast volatility more efficiently. In the past more than two decades, the non-linear models have been widely used by various researchers who have found different combinations of AR-GARCH models appropriate for different situations (Jordaan *et al*., 2007; Paul *et al*., 2009; Sundaramoorthy *et al*., 2014). But, the most widely used GARCH specification is the GARCH (1, 1) model in the time-series forecasting.

In recent years, various time-series have shown both symmetric and asymmetric patterns. The GARCH model due to its nature of dealing with only magnitude not the positivity or negativity of the shocks, has turned out to be relatively inefficient to model and forecast such series. Thus, the need for extension of the GARCH family model was felt and was first answered by Nelson (1991) in the form of exponential GARCH (EGARCH) model, which not only considers the magnitude of the shock but also its negativity and positivity. The asymmetric models provide an explanation for the so called leverage effect, i.e. an unexpected price drop increases volatility more than an analogous unexpected price increase. A good description of these models has been given by Fan and Yao (2003) and Tsay (2005).

ARIMA Model

A generalization of ARMA models which incorporates a wide class of non-stationary time-series is obtained by introducing the differencing into the model. The simplest example of a non-stationary process which reduces to a stationary one after differencing is Random Walk. A process $\{y_t\}$ is said to follow an Integrated ARMA model, denoted by ARIMA (*p*, *d*, *q*), if $\nabla^d y_t = (1-B)^d \varepsilon_t$ is ARMA (*p*, *q*). The model is written as Equation (1):

$$\varphi(B)(1-B)^d y_t = \theta(B)\varepsilon_t \qquad \ldots(1)$$

where, $\varepsilon_t \sim WN(0,\sigma^2)$, and *WN* indicates white noise. The integration parameter *d* is a non-negative integer. When $d = 0$, ARIMA $(p, d, q) \equiv$ ARMA (p, q).

The ARIMA methodology is carried out in three stages, viz. identification, estimation and diagnostic checking. Parameters of the tentatively selected ARIMA model at the identification stage are estimated at the estimation stage and adequacy of tentatively selected model is tested at the diagnostic checking stage. If the model is found to be inadequate, the three stages are repeated until satisfactory ARIMA model is selected for the time-series under consideration. An excellent discussion of various aspects of this approach is given in Box *et al*. (2007). Most of the standard software packages, like SAS, SPSS and EViews contain programs for fitting of ARIMA models.

GARCH Model

The ARCH(q) model for the series $\{\varepsilon_t\}$ is defined by specifying the conditional distribution of ε_t given the information available up to time t-1. Let ψ_{t-1} denote this information. ARCH (q) model for the series $\{\varepsilon_t\}$ is given by

$$\varepsilon_t / \psi_{t-1} \sim N(0, h_t) \qquad \ldots(2)$$

$$h_t = a_0 + \sum_{i=1}^{q} a_i \varepsilon_{t-i}^2 \qquad \ldots(3)$$

where, $a_0 >, a_i \geq 0$, for all i and $\sum_{i=1}^{q} a_i < 1$ are required to be satisfied to ensure non-negative and finite unconditional variance of stationary $\{\varepsilon_t\}$ series.

However, ARCH model has some drawbacks. Firstly, when the order of ARCH model is very large, estimation of a large number of parameters is required. Secondly, conditional variance of ARCH(q) model has the property that unconditional autocorrelation function (ACF) of squared residuals; if it exists, decays very rapidly compared to what is typically observed, unless maximum lag q is large. To overcome the weaknesses of ARCH model, Bollerslev (1986) proposed the Generalized ARCH (GARCH) model in which conditional variance is also a linear function of its own lags and has the following form :

$$\varepsilon_t = \xi_t h_t^{1/2}$$

$$h_t = a_0 + \sum_{i=1}^{q} a_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} b_j h_{t-j} \quad \ldots(4)$$

where, $\xi_t \sim$ IID($0,1$). A sufficient condition for the conditional variance to be positive is:

$$a_0 > 0,\ a_i \geq 0,\ i = 1,2,...,q.\ b_j \geq 0,\ j = 1,2,...,\ p$$

The GARCH (p, q) process is weakly stationary if and only if

$$\sum_{i=1}^{q} a_i + \sum_{j=1}^{p} b_j < 1.$$

The conditional variance defined by Equation (4) has the property that the unconditional autocorrelation function of ε_t^2; if it exists, can decay slowly. For the ARCH family, the decay rate is too rapid compared to what is typically observed in financial time-series, unless the maximum lag q is long. As Equation (4) is a more parsimonious model of the conditional variance than a high-order ARCH model, most users prefer it to the simpler ARCH alternative.

The most popular GARCH model in applications is the GARCH (1,1) model. To express GARCH model in terms of ARMA model, we denote $\eta_t = \varepsilon_t^2 - h_t$. Then from Equation (4), we get,

$$\varepsilon_t^2 = a_0 + \sum_{i=1}^{Max(p,q)} (a_i + b_i)\varepsilon_{t-i}^2 + \eta_t + \sum_{j=1}^{p} b_j \eta_{t-j} \quad \ldots(5)$$

Thus, a GARCH model can be regarded as an extension of the ARMA approach to squared series $\{\varepsilon_t^2\}$. Using the unconditional mean of an ARMA model, we have

$$E(\varepsilon_t^2) = \frac{a_0}{1 - \sum_{i=1}^{Max(p,q)} (a_i + b_i)} \quad \ldots(6)$$

which shows that the denominator of the prior fraction is positive.

EGARCH Model

The EGARCH model was developed to allow for asymmetric effects between positive and negative shocks on the conditional variance of future observations. Another advantage, as pointed out by Nelson and Cao (1992), is that there are no restrictions on the parameters. In the EGARCH model, the conditional variance, h_t, is an asymmetric function of lagged disturbances. The model is given by

$$\varepsilon_t = \xi_t h_t^{1/2},$$

$$\ln(h_t) = a_0 + \frac{1 + b_1 B + \ldots + b_{q-1} B^{q-1}}{1 - a_1 B + \ldots + a_p B^p} g(\varepsilon_{t-1}) \quad \ldots(7)$$

where,

$$g(\varepsilon_t) = \begin{cases} (\theta + \gamma)\varepsilon_t - \gamma E(|\varepsilon_t|), & if \ \ \varepsilon_t \geq 0, \\ (\theta - \gamma)\varepsilon_t - \gamma E(|\varepsilon_t|), & if \ \ \varepsilon_t < 0, \end{cases}$$

B is the backshift (or lag) operator such that

$$Bg(\varepsilon_t) = g(\varepsilon_{t-1})$$

The EGARCH model can also be represented in another way by specifying the logarithm of conditional variance as

$$\ln(h_t) = a_0 + \beta \ln(h_{t-1}) + \alpha \left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right| + \gamma \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \quad \ldots(8)$$

This implies that the leverage effect is exponential, rather than quadratic, and the forecasts of the conditional variance are guaranteed to be non-negative. Karanasos and Kim (2003) have carried out a detailed analysis of moment's structure of the ARMA-EGARCH model, while Kobayashi and Shi (2005) have studied the testing for EGARCH against stochastic volatility models.

Akaike Information Criterion and Bayesian Information Criterion

Standard model evaluation criteria, such as Akaike information criterion (AIC) and Bayesian information criterion (BIC), are used to compare the performance of different models. These criteria penalize the decrease in the degrees of freedom when more variables are added. For ARIMA model, it is calculated as follows :

$$\text{AIC} = T' \quad \log(\sigma^2) + \quad 2 \quad (p+q+1)$$

$$\text{BIC} = T' \quad \log(\sigma^2) + \quad (p+q+1)\log T'$$

where, T' denotes the number of observations used for the estimation of parameters and σ^2 denotes the mean square error.

The AIC and BIC values for GARCH model with Gaussian distributed errors are computed by:

$$\text{AIC} = 2 \log \textit{(likelihood)} + 2T$$

$$\text{BIC} = 2 \log \textit{(likelihood)} + \log \textit{(Tk)}$$

where, k is model degrees of freedom.

The AIC and BIC values for EGARCH model with Gaussian distributed errors are computed by :

$$\text{AIC} = \sum_{t=1}^{T} \left(\log h_t + \varepsilon_t^2 h_t^{-1} \right) + 2(\text{p} + \text{q} + 1)$$

$$\text{BIC} = \sum_{t=1}^{T} \left(\log h_t + \varepsilon_t^2 h_t^{-1} \right) + 2(\text{p} + \text{q} + 1) \log(\text{T} - \text{k} + 1)$$

where notations have usual meaning as defined earlier.

Empirical Results

Data and Implementation

In this study, three sets of data were used to evaluate the forecasting ability of different models. The series included domestic and international edible oils price indices as well as international cotton price, ‘Cotlook A’ index. The Cotlook A index which represents international prices of raw cotton was collected from the commodity price bulletin, published by the United Nations Convention of Trade and Development (UNCTAD). The international edible oils price data were collected from the World Bank Commodity Prices Indices (Pink Sheet) available at its official website. The data for domestic edible oils price index were collected from the Office of the Economic Adviser, Ministry of Commerce, Government of India. These series illustrate the complexity and variation of typical agricultural price data (Figures 1-3). Each series contained 360 data points (April, 1982 to March, 2012), of which, first 348 data points were used for model building purpose and the rest 12 data points were kept for validation, except for the Cotlook A series in which 346 data points were used for modelling and the remaining 14 points for forecasting. This variation for validation points was done to properly depict the effect of asymmetric EGARCH model. The characteristics of the data sets used are presented in the Table 1.

The visual inspection of these series (Figures 1-3) clearly suggests that volatility was present at several time-epochs. Moreover, the skewness and kurtosis coefficients of Cotlook A index suggested the asymmetry and fat-tailed distribution of the series (Table 1). The literature suggests that ARCH/GARCH models are appropriate for quantifying price volatility (Jordaan *et al*., 2007), as these models have two major advantages over the ARIMA and other linear models. Firstly, the predictable and unpredictable components of the price process can be classified easily. Secondly, the heterocedasticy is considered as the variance to be modelled not as a problem. Thus, GARCH was preferred over the ARIMA model in our study.

Stationarity Test

The basic assumption in time-series econometrics is that the underlying series is stationary in nature. Thus, the test for stationarity of the three series under consideration was done using Augmented Dickey Fuller (ADF) and Phillips-Perron (PP) test statistics. The ADF test relies on parametric transformation of the model, while PP test uses non-parametric statistical methods to take care of the serial correlation in the error-terms. For all the three series, both the tests were

Table 1. Summary statistics of price series

Statistic	Domestic edible oils price index	International edible oils price index	Cotlook A price index
Mean	74.47	112.95	157.24
Median	72.57	100.11	149.68
Maximum	141.60	256.22	506.34
Minimum	25.22	64.13	81.93
Standard deviation	30.31	41.37	51.66
Skewness	0.16	1.64	3.03
Kurtosis	2.12	5.16	17.84

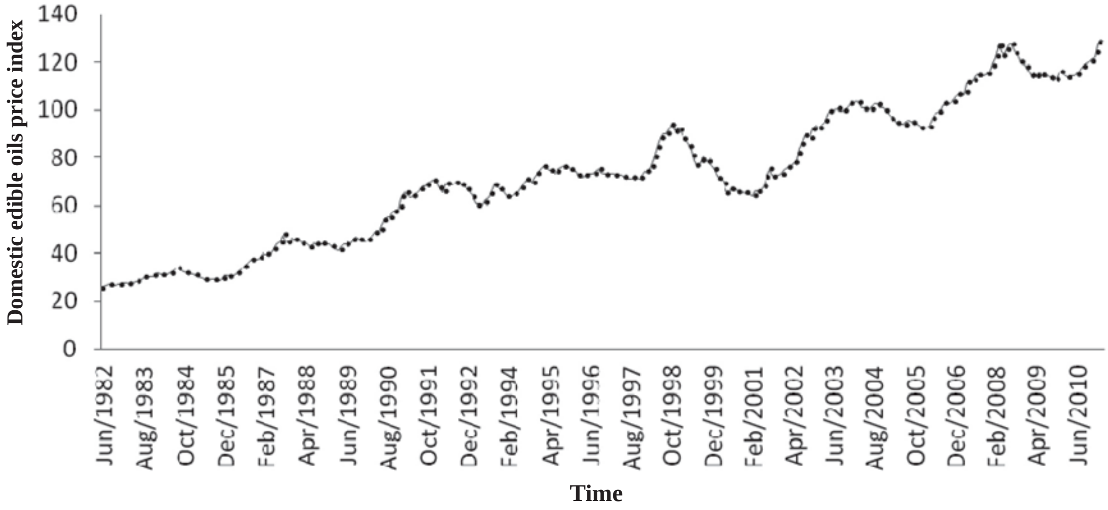

Figure 1. Fitted AR (2) – GARCH (1, 1) model along with its data points, 1982-2010

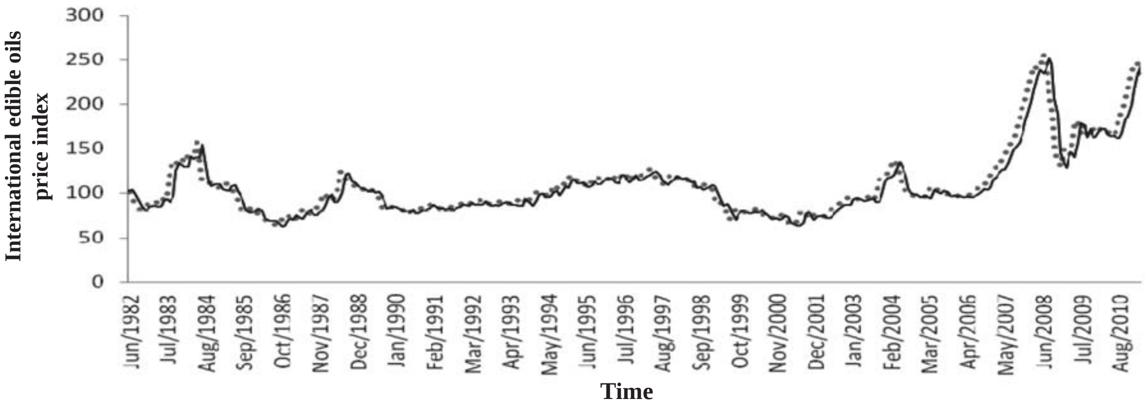

Figure 2. Fitted AR (2) – GARCH (1, 1) model along with its data points, 1982-2010

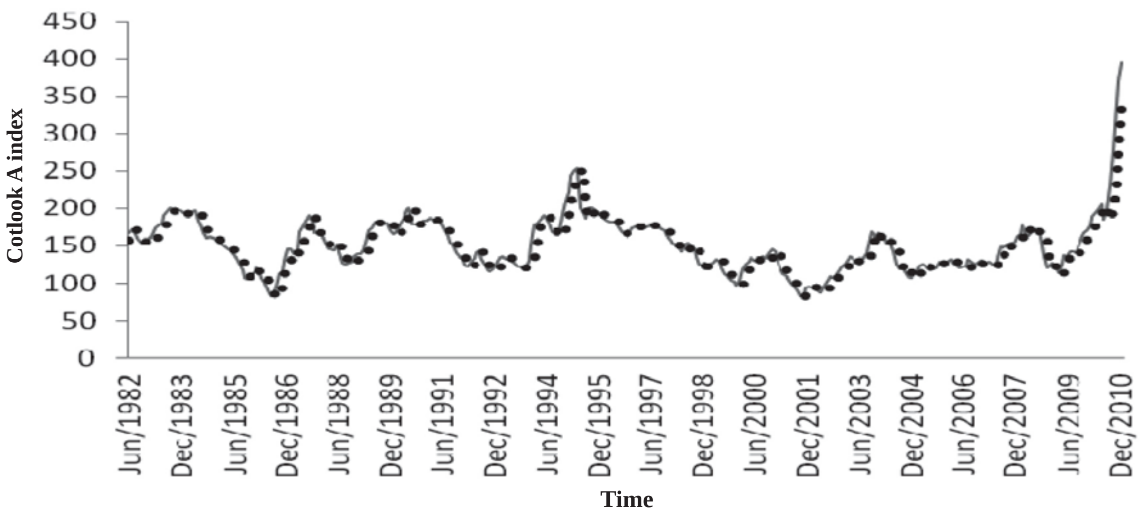

Figure 3. Fitted AR (2) – GARCH (1, 1) model along with its data point, 1982-2010

Table 2. Stationarity tests for different price series

Series		ADF test	P value	PP test	P value
Domestic edible oils price index	Level	0.20	0.97	0.001	0.95
	Differenced	12.69	<0.001	13.25	<0.001
International edible oils price index	Level	1.48	0.58	1.25	0.65
	Differenced	12.09	<0.001	12.16	<0.001
Cotlook A index	Level	0.99	0.29	0.84	0.35
	Differenced	10.20	<0.001	9.05	<0.001

found insignificant at 5 per cent level of significance, thus confirming the non-stationarity of the level series. But, on differencing the series once, both the tests were found highly significant at 1 per cent level of significance confirming their stationarity. Thus, the need of first differencing of the series was felt for proper modelling and forecasting of these series. The detailed results of the tests are given in Table 2.

Fitting of ARIMA Model

Various combinations of the ARIMA models were tried after first differencing of all the three series. Among all, the AR (1) model had minimum AIC and BIC values for all the series. As, the root mean square error (RMSE) values of series were quite high, it confirmed that the ARIMA cannot model and forecast volatile data efficiently. In addition, the square of the residuals of these series had significant autocorrelation. Thus, the need of modelling these series with nonlinear models of the GARCH family was felt. The parameter estimates of the ARIMA model along with the standard errors in bracket are given in Table 3.

Testing of ARCH Effect

The Box-Jenkins approach has a basic assumption that the residuals remain constant over time. Thus, the ARCH – Lagrange multiplier (LM) test was carried out on the square of the residuals obtained after fitting the ARIMA model on all the three series to test whether residuals do in fact remain constant. The results of the test revealed the presence of ARCH effect for all the three series. The results of the test are given in Table 4.

Fitting of GARCH Model

The GARCH model was fitted to all the three price series and then forecasting was done. For all the three series, the AR(2)-GARCH(1,1) model was identified to be the best model on the basis of in-sample performance. The estimates of the parameters of the AR(2)-GARCH(1,1) model along with their standard errors in brackets for individual series are given in Table 5. It is worth mentioning that after modelling the variance as well, the mean model changes from AR(1) to AR(2). The results have revealed that domestic and international edible oils price indices exhibit a high persisting volatility as the sum of *a* and *b* are close to one. The good fit of the model for both domestic and international edible oils price indices is depicted clearly by Figure 1 and Figure 2, respectively for both the series. The modelling of Cotlook A index series was not satisfactory, where a sudden rise in the volatility was seen with the help of Figure 3. As indicated earlier, the asymmetric nature of the series was also evident from the coefficients of skewness and kurtosis (Table 1). This motivated us to model and forecast the Cotlook A series using EGARCH model.

Table 3. Parameter estimates of ARIMA(1,1,0) Model

Series	Parameter	Estimate	P value
Domestic edible oils price index	AR(1)	0.38 (0.048)	< 0.0001
International edible oils price index	AR(1)	0.42 (0.049)	< 0.0001
Cotlook A index	AR(1)	0.56 (0.050)	< 0.0001

Note: The values within the parentheses are the corresponding standard errors.

Table 4. ARCH - LM test for all the three series

Lags	Q value			P value
	Domestic edible oils price index	International edible oils price index	Cotlook A index	
1	336.32	309.32	179.55	< 0.0001
2	656.57	550.00	253.21	< 0.0001
3	962.50	724.16	290.18	< 0.0001
4	1256.64	843.79	303.43	< 0.0001
5	1538.86	921.25	305.74	< 0.0001
6	1808.99	970.81	306.06	< 0.0001

Table 5. Parameter estimates of AR(2)-GARCH(1,1) model

Series	a	b	AIC value
Domestic edible oils price index	0.09 (0.03)	0.88 (0.03)	1191.90
International edible oils price index	0.40 (0.07)	0.54 (0.06)	2091.03
Cotlook A index	0.20 (0.09)	0.45 (0.05)	2288.88

Note: The values within the parenthesis are the corresponding standard errors.

Fitting of EGARCH Model

To capture the asymmetric nature of volatility in the data, EGARCH model was employed. The mean equation of fitted AR(2)-EGARCH(1,1) model was :

$$y_t = \underset{(4.71)}{149.01} - \underset{(0.05)}{1.40}\, y_{t-1} + \underset{(0.05)}{0.45}\, y_{t-2} + \varepsilon_t$$

where,

$$\varepsilon_t = h_t^{1/2}\eta_t$$

and h_t satisfies the variance equation

$$h_t = \underset{(0.11)}{0.37} + \underset{(0.04)}{0.87}\ln(h_{t-1}) + \underset{(0.12)}{0.54}\left|\varepsilon_{t-1}/\sqrt{h_{t-1}}\right| + \underset{(0.16)}{0.50}\,\varepsilon_{t-1}/\sqrt{h_{t-1}}$$

The values in the brackets for both the mean and variance equations indicate the standard- errors of the estimates. The AIC value for fitted EGARCH model is 2279.45, which is less than the corresponding value, 2288.88 for the fitted GARCH model. This clearly shows the superiority of EGARCH model over GARCH model for the data under consideration for modelling purposes. Fitted EGARCH model along with data is exhibited in Figure 4. Evidently, the fitted model was able to capture quite well the volatility present at time-epochs, especially towards the end.

Forecasting

The one-step ahead forecasts for the monthly index of the domestic edible oils price index for the period April, 2011 to March, 2012 along with its corresponding standard errors in brackets are given in Table 6. The forecasting ability of both the models were judged on the basis of root mean square error (RMSE) and relative mean absolute prediction error (RMAPE) and is reported in Table 7. The one-step ahead forecasts for the monthly international edible oils price for the period April, 2011 to March, 2012 along with its corresponding standard errors in brackets are given in Table 8. The forecasting ability of both the models were judged on the basis of root mean square error (RMSE) and relative mean absolute prediction error (RMAPE) and is reported in Table 9.

The one-step ahead forecasts for the monthly Cotlook A index for the period February, 2011 to March, 2012 along with its corresponding standard errors in bracket is given in Table 10. The forecasting capability of the three models was judged on the basis of the root mean square error (RMSE) and relative mean absolute prediction error (RMAPE) and is reported in Table 11.

The results have clearly indicated that as the Cotlook A index series has depicted a high volatility

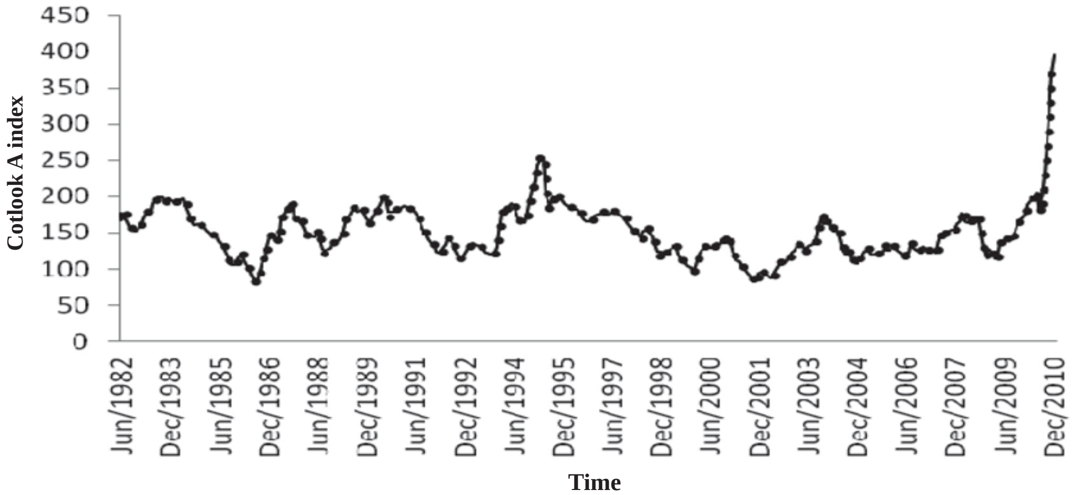

Figure 4. Fitted AR (2) – EGARCH (1, 1) model along with its data points

Table 6. Forecast of domestic edible oils price index series (Period: April 2011 to March 2012)

Month	Actual value	Forecast value	
		ARIMA (1,1,0)	AR(2)-GARCH(1,1)
Apr-11	129.70	128.75 (1.37)	128.90 (1.57)
May-11	132.10	128.92 (2.33)	129.27 (1.57)
Jun-11	133.40	129.17 (3.13)	129.74 (1.57)
Jul-11	133.70	129.45 (3.80)	130.26 (1.56)
Aug-11	135.60	129.74 (4.38)	130.79 (1.56)
Sep-11	136.30	130.04 (4.90)	131.33 (1.56)
Oct-11	135.40	130.33 (5.37)	131.88 (1.56)
Nov-11	135.30	130.63 (5.80)	132.43 (1.56)
Dec-11	137.00	130.92 (6.21)	132.98 (1.56)
Jan-12	139.20	131.22 (6.59)	133.53 (1.56)
Feb-12	139.30	131.52 (6.95)	134.09 (1.56)
Mar-12	141.60	131.81 (7.23)	134.65 (1.56)

Note: The values within the parentheses are the corresponding standard errors.

Table 7. Forecast evaluation of the domestic edible oils price index series

Model	Root mean square error	Relative mean absolute prediction error (%)
ARIMA(1,1,0)	1.71	4.10
AR(2)-GARCH(1,1)	1.25	2.96

Table 8. Forecast of the international edible oils price index series (Period: April 2011 to March 2012)

Month	Actual value	Forecast value	
		ARIMA (1,1,0)	AR(2)-GARCH(1,1)
Apr-11	227.73	224.058 (6.07)	227.72 (10.78)
May-11	228.26	221.59 (10.53)	226.39 (10.64)
Jun-11	225.25	220.75 (14.30)	225.08 (10.51)
Jul-11	222.90	220.60 (17.51)	223.77 (10.38)
Aug-11	221.38	220.73 (20.31)	222.49 (10.26)
Sep-11	216.79	220.98 (22.81)	221.21 (10.14)
Oct-11	203.13	221.28 (25.07)	219.95 (10.03)
Nov-11	204.64	221.60 (27.15)	218.71 (9.92)
Dec-11	199.87	221.92 (29.08)	217.48 (9.82)
Jan-12	208.08	222.26 (30.89)	216.26 (9.73)
Feb-12	215.89	222.59 (32.06)	215.05 (9.63)
Mar-12	226.80	222.92 (34.23)	223.84 (9.55)

Note: The values within the parentheses are the corresponding standard errors.

Table 9. Forecast evaluation of the international edible oils price index series

Model	Root mean square error	Relative mean absolute prediction error (%)
ARIMA (1,1,0)	3.19	3.90
AR(2)-GARCH (1,1)	2.48	2.78

Table 10. Forecast of the Cotlook A index series (Period: February 2011 to March 2012)

Month	Actual value	Forecast value		
		ARIMA(1,1,0)	AR(2)-GARCH(1,1)	AR(2)-EGARCH(1,1)
Feb-11	469.98	408.34 (8.30)	389.59 (26.46)	391.77 (22.11)
Mar-11	506.34	416.47 (15.56)	371.55 (25.74)	376.72 (18.12)
Apr-11	477.56	421.40 (22.35)	348.54 (25.05)	356.74 (15.36)
May-11	364.91	424.53 (28.55)	324.69 (24.39)	335.61 (13.39)
Jun-11	317.75	426.66 (34.17)	301.98 (23.75)	315.13 (11.94)
Jul-11	268.96	428.23 (39.29)	281.25 (23.13)	296.14 (10.87)
Aug-11	251.55	429.49 (43.97)	262.76 (22.54)	278.91 (10.04)
Sep-11	257.63	430.57 (48.29)	246.50 (21.97)	263.48 (9.41)
Oct-11	243.85	431.55 (52.30)	232.32 (21.42)	249.78 (8.91)
Nov-11	230.78	432.48 (56.05)	220.01 (20.90)	237.66 (8.52)
Dec-11	210.43	433.37 (59.58)	209.35 (20.39)	226.96 (8.21)
Jan-12	222.91	434.25 (54.45)	200.15 (19.91)	217.55 (7.96)
Feb-12	222.12	435.12 (57.13)	192.21 (19.44)	209.26 (7.76)
Mar-12	219.36	435.99 (59.68)	185.37 (19.01)	201.97 (7.59)

Note: The values within the parentheses are the corresponding standard errors.

Table 11. Forecast evaluation of the Cotlook A index series

Model	Root mean square error	Relative mean absolute prediction error (%)
ARIMA(1,1,0)	44.03	60.72
AR(2)-GARCH(1,1)	15.38	9.36
AR(2)-EGARCH(1,1)	14.41	3.99

in the months of February, March and April of 2011, the respective standard error of EGARCH model was high and as the volatility decreased in the remaining months, the corresponding standard error also decreased. This feature was not observed in the GARCH model where the standard error followed a decreasing trend, irrespective of the volatility. In addition, the point forecast of EGARCH model for June, 2011 and November, 2011 was much closer to the actual value and far better than the competing GARCH model. Lastly, from the viewpoint of interval prediction, it may be noted from Table 10 that, for the fitted EGARCH model, the actual values during May, 2011 to March, 2012 lay closely within the 95 per cent prediction-interval which was not observed in the GARCH model

Conclusions

The performance of ARCH model and its modifications, namely GARCH and EGARCH has been studied using monthly agricultural commodity price indices. The domestic and international edible oils price indices have been modelled and forecasted using ARIMA and GARCH models. For both the series, the AR(2)-GARCH (1,1) has outperformed the ARIMA(1,1,0) model in terms of forecasting accuracy. The superiority of the GARCH model for modelling the series is highlighted by the lower AIC values than the corresponding ARIMA model and high forecasting accuracy has been assured by low RMSE and RAMPE values.

The AR-GARCH model has given better point forecast than the competing ARIMA model for both the price indices. The GARCH model has forecasted the volatility better than the ARIMA model in one-step ahead forecast towards the end. Further, in view of a sudden spike in Cotlook A index series, EGARCH was employed in addition to ARIMA and GARCH models in order to capture asymmetry pattern of the data. The EGARCH model has outperformed the GARCH and ARIMA models for the present data set as far as modelling and forecasting is concerned in terms of RMSE and RMAPE values. Hence, the empirical results have supported the theory that EGARCH model can capture asymmetric volatility. The methodology employed in this paper can also be used for forecasting other agricultural time-series data showing volatility.

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