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GARCH Nonlinear Time Series Analysis for Modelling and Forecasting of India's Volatile Spices Export Data

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SUMMARY

Modelling and forecasting of India's spices export data set, which exhibits a volatile behaviour, is first attempted through the Box-Jenkins Autoregressive integrated moving average (ARIMA) approach. Subsequently, Generalized autoregressive conditional heteroscedastic (GARCH) nonlinear time-series model along with its estimation procedures are thoroughly studied. Lagrange multiplier test for testing presence of Autoregressive conditional heteroscedastic (ARCH) effects is also discussed. The GARCH model is employed for modelling and forecasting of the data. Comparative study of the fitted ARIMA and GARCH models is carried out from the viewpoint of dynamic one-step ahead forecast error variance along with Mean square prediction error (MSPE), Mean absolute prediction error (MAPE) and Relative mean absolute prediction error (RMAPE). The SAS and EViews, Ver. 4 software packages along with computer programs in C are used for data analysis. Superiority of GARCH model over ARIMA approach is demonstrated for the data under consideration. Possible use of more accurate forecasts obtained by GARCH methodology vis-à-vis ARIMA approach is briefly discussed.

Keywords: ARIMA, EViews software package, Generalized autoregressive conditional heteroscedastic model, Monthly export data of spices, SAS software package, Volatility.

1. INTRODUCTION

Spices are the most important commercial crops of our country. The important spices extensively grown in India are cardamom, pepper, chillies, turmeric, and ginger. With respect to production, consumption and export of spices, India ranks first in the World. The total area in India under these spices is over one million hectares, and these accounted for an annual export of about Rs. 3330 crores during the year 2006-07. In short, India commands a formidable position in the World spices trade with 47% share in volume and 40% in value. More than 150 value-added products of spices are currently available for export. The most important among these are spice oils and oleoresins. More than 70% of their total World supply is from India. The target set by Government of India is to increase the spices export by ten-folds in the next ten years. To achieve such an ambitious target, the twin goals of spice sector should be to enhance the annual growth rate from 13% to 20% and share of export of value-added spice products from 58% to 75%. As emphasized by Jaffee (2005), volatility seems to be the norm rather than the exception in international markets for spices due to the structure of the trade, climatic conditions, and the rapidity with which producers can respond to price changes. Proper monitoring and appropriate policy measures require efficient modelling and forecasting of spices time-series data.

The most widely used technique for analysis of time-series data is, undoubtedly, the Box Jenkins

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Autoregressive integrated moving average (ARIMA) methodology. However, it is based on some crucial assumptions, like linearity, stationarity, and homoscedastic errors. Further, time-series data quite often exhibit features which can not be explained by ARIMA model, which is "linear". As an example, the famous time-series of average monthly sunspot numbers exhibits a cyclical behaviour in such a way that the series generally increases at a faster rate than it decreases. Similarly, asymmetric phenomenon arises with economic series, which tend to behave differently when the economy is moving into recession rather than when coming out of it. Many financial time-series show periods of stability, followed by unstable periods with high volatility. The loss in continuing to use the age-old ARIMA methodology is that this type of behaviour can not be explained satisfactorily, and so "nonlinear time-series models" are usually needed to describe data sets in which variance changes through time. The search for an appropriate model of this type would lead to a greater insight into the underlying mechanism. An excellent description of these and other related issues is given in Chatfield (2001).

During last two decades or so, the area of Nonlinear time-series modelling has been rapidly developing. The most promising parametric nonlinear time-series model has been the Autoregressive conditional heteroscedastic (ARCH) model, which was introduced by Engle (1982), and for which he was awarded the prestigious Nobel Prize in Economics in 2003. This entails a completely different class of models which is concerned with modelling volatility. The objective is not to give better point forecasts but rather to give better estimates of the variance which, in turn, allows more reliable forecast intervals leading to a better assessment of risk (Chatfield 2001). The ARCH model allows the conditional variance to change over time as a function of squared past errors leaving the unconditional variance constant. The presence of ARCH-type effects in financial and macro-economic time series is a well established fact. The combination of ARCH specification for conditional variance and the Autoregressive (AR) specification for conditional mean has many appealing features, including a better specification of the forecast error variance. Ghosh and Prajneshu (2003) employed AR(p)-ARCH(q)-in-Mean model for carrying out modelling and forecasting of volatile monthly onion price data. The AR-ARCH model has also been used as the basic "building blocks" for Markov switching and mixture models (See e.g. Lanne and Saikkonen 2003, and Wong and Li 2001). Various aspects of the family of mixtures of ARCH models have been thoroughly investigated by Ghosh *et al.* (2005, 2006).

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 these difficulties, Bollerslev (1986) proposed the Generalized ARCH (GARCH) model in which conditional variance is also a linear function of its own lags. This model is also a weighted average of past squared residuals, but it has declining weights that never go completely to zero. It gives parsimonious models that are easy to estimate and, even in its simplest form, has proven surprisingly successful in predicting conditional variances. Angelidis *et al.* (2004) used GARCH model for describing Value-at-Risk.

In this paper, our purpose is to thoroughly study the GARCH model and its estimation procedures. Subsequently, this model along with the Box Jenkins ARIMA model is applied to describe the volatility of monthly export of spices from India during the period April 2000 to August 2006. Finally, the performance of one-step ahead forecasting for three months, i.e. from September 2006 to November 2006 by both the models is examined.

2. DESCRIPTION OF MODELS

2.1 The ARIMA Model

The Autoregressive moving average (ARMA) model, denoted as ARMA(p, q), is given by

$$y_t = \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \ldots + \varphi_p y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots - \theta_q \varepsilon_{t-q} \qquad (2.1)$$

or equivalently by

$$\varphi(B) y_t = \theta(B) \varepsilon_t \qquad (2.2)$$

where

$$\varphi(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \ldots - \varphi_p B^p$$

and

$$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - ... - \theta_q B^q$$

In the above, B is the backshift operator defined by $By_t = y_{t-1}$. A generalization of ARMA models, which incorporates a wide class of nonstationary time-series, is obtained by introducing "differencing" in the model. The simplest example of a nonstationary process which reduces to a stationary one after differencing is "Random Walk". A process $\{ y_t \}$ is said to follow Autoregressive integrated moving average (ARIMA), 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

$$\varphi(B)(1 - B)^d y_t = \theta(B)\varepsilon_t \quad (2.3)$$

where ε_t are identically and independently distributed as $N(0, \sigma^2)$. The integration parameter d is a nonnegative integer. When $d = 0$, the ARIMA(p, d, q) model reduces to ARMA(p, q) model.

2.2 The GARCH Model

The ARCH(q) model for the series $\{\varepsilon_t\}$ is given by

$$\varepsilon_t | \psi_{t-1} \sim N(0, h_t) \quad (2.4)$$

Here ψ_{t-1} denotes information available up to time $t - 1$, and

$$h_t = a_0 + \sum_{i=1}^{q} a_i \varepsilon_{t-i}^2 \quad (2.5)$$

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

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

$$h_t = a_0 + \sum_{i=1}^{q} a_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} b_j h_{t-j} \quad (2.6)$$

A sufficient condition for the conditional variance to be positive is

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

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 most popular GARCH model in applications is the GARCH(1, 1) model. To express GARCH model in terms of ARMA model, denote $\eta_t = \varepsilon_t^2 - h_t$. Then from eq. (2.6)

$$\varepsilon_t^2 = a_0 + \sum_{i=1}^{Max(p,q)} (a_i + b_i)\varepsilon_{t-i}^2 + \eta_t + \sum_{j=1}^{p} b_j \eta_{t-j} \quad (2.7)$$

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

2.3 Estimation of Parameters

Estimation of parameters for ARIMA model is generally done through Nonlinear least squares method. Fortunately, several software packages are available for fitting of ARIMA models. In this paper, SAS, Ver. 9.1 software package is used. The Akaike information criterion (AIC) and Bayesian information criterion (BIC) values for ARIMA model are computed by

$$AIC = T'\log(\sigma^2) + 2(p + q + 1) \quad (2.8)$$

and

$$BIC = T'\log(\sigma^2) + (p + q + 1)\log T' \quad (2.9)$$

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

In order to estimate the parameters of GARCH model, Method of maximum likelihood is used. The loglikelihood function of a sample of T observations, apart from constant, is

$$L_T(\theta) = T^{-1}\sum_{t=1}^{T}\left(\log h_t + \varepsilon_t^2 h_t^{-1}\right)$$

where

$$h_t = a_0 + \sum_{i=1}^{q} a_i y_{t-i}^2 + \sum_{j=1}^{p} b_j\ h_{t-j}$$

If $f(.)$ denotes the probability density function of ε_t, generally, maximum likelihood estimators are derived by minimizing

$$L_T(\theta) = T^{-1}\sum_{t=v}^{T}\left(\log\sqrt{\tilde{h}_t} - \log \quad f(\varepsilon_t/\sqrt{\tilde{h}_t})\right)$$

where $\tilde{h}_t$ is the truncated version of h_t (Fan and Yao 2003). For heavy tailed error distribution, Peng and Yao (2003) proposed Least absolute deviations estimation (LADE), which minimizes $\sum_{t=v}^{T}\left|\log\varepsilon_t^2 - \log(h_t)\right|$, where $v = p + 1$, if $q = 0$ and $v > p + 1$, if $q > 0$. Fan and Yao (2003) and Straumann (2005) have given a good description of various estimation procedures for conditionally heteroscedastic time-series models.

The Akaike information criterion (AIC) and Bayesian information criterion (BIC) values for GARCH model with Gaussian distributed errors are computed by

$$\text{AIC}= \sum_{t=1}^{T}\left(\log\tilde{h}_t + \varepsilon_t^2\tilde{h}_t^{-1}\right) + 2(p + q + 1) \qquad (2.10)$$

and

$$\text{BIC} = \sum_{t=1}^{T}\left(\log\tilde{h}_t + \varepsilon_t^2\tilde{h}_t^{-1}\right) + 2(p + q + 1)\log(T - v + 1) \qquad (2.11)$$

where T is the total number of observations.

Evidently, the likelihood equations are extremely complicated. Fortunately, the estimates can be obtained by using a software package, like EViews, SAS, SPLUS GARCH, GAUSS, TSP, MATLAB, and RATS. In the present investigation, the Gaussian maximum likelihood estimation procedure available in EViews software package, Ver. 4 is used for data analysis. Further, AIC and BIC values for ARIMA and GARCH models are computed separately by writing computer programs in C.

2.4 Testing for ARCH Effects

Let $\varepsilon_t = y_t - \phi y_{t-1}$ be the residual series. The Lagrange multiplier (LM) test for squared series $\{\varepsilon_t^2\}$ may be used to check for conditional heteroscedasticity. The test is equivalent to usual F-statistic for testing $H_0 : a_i = 0,\ i = 1, 2, ..., q$ in the linear regression

$$\varepsilon_t^2 = a_0 + a_1\varepsilon_{t-1}^2 + ... + a_q\varepsilon_{t-q}^2 + e_t,\ t = q + 1,..., T \qquad (2.12)$$

where e_t denotes the error term, q is the prespecified positive integer, and T is the sample size. Let $SSR_0 = \sum_{t=q+1}^{T}\left(\varepsilon_t^2 - \bar{\omega}\right)^2$, where $\bar{\omega} = \sum_{t=q+1}^{T}\varepsilon_t^2/T$ is sample mean of $\{\varepsilon_t^2\}$, and $SSR_1 = \sum_{t=q+1}^{T}\hat{e}_t^2$, where $\hat{e}_t$ is the least square residual of eq. (2.12). Then, under H_0, the ARCH-LM test statistic, viz.

$$F = \frac{(SSR_0 - SSR_1)/q}{SSR_1/(T - q - 1)} \qquad (2.13)$$

follows asymptotically the chi-squared distribution with q degrees of freedom.

3. MODELLING OF INDIA'S SPICES EXPORT DATA

All-India data of monthly export of spices during the period April 2000 to November 2006 are obtained from Indiastat (www.indiastat.com) available at I.A.S.R.I., New Delhi and the same are exhibited in Fig. 1. From the total 80 data points, first 77 data points corresponding to the period April 2000 to August 2006 are used for building the model and remaining are used for validation purpose. A perusal of the data shows that, during the period from April 2004 to February 2006, these varied between Rs 143 crores and Rs 189 crores. Then the spices export suddenly jumped almost 80% to the level of Rs 345 crores in March 2006, which was followed

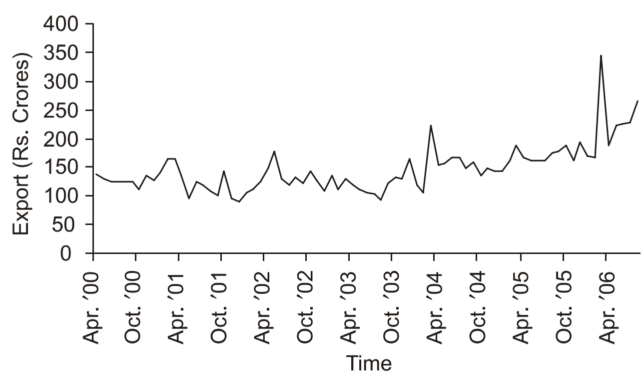

Fig. 1. Data of monthly spices export from India

by a sudden dip to as low as Rs 188 crores in the very next month. All this clearly shows that volatility was present during March 2006. Similar type of presence of volatility was noticed at several other time-epochs, like May 2001, August 2001, and June 2002.

3.1 Fitting of ARIMA Model

A perusal of estimated autocorrelation functions (acf) of original series, reported in Table 1, shows that it decays very slowly, implying thereby that this series

Table 1. Sample autocorrelation functions (acf) and partial autocorrelation functions (pacf) of the original and differenced series

Lag	acf of the series	pacf of the series	acf of the differenced series	pacf of the differenced series
1	0.550	0.550	–0.498	–0.498
2	0.525	0.319	–0.048	–0.393
3	0.539	0.267	0.188	–0.065
4	0.405	–0.022	–0.197	–0.181
5	0.457	0.147	0.079	–0.110
6	0.303	–0.148	0.042	–0.040
7	0.274	–0.023	–0.009	0.069
8	0.251	–0.039	–0.008	0.049
9	0.211	0.053	0.000	0.040
10	0.202	0.001	–0.058	–0.064
11	0.214	0.121	–0.007	–0.120
12	0.239	0.102	0.105	0.014
13	0.182	–0.031	–0.078	–0.009
14	0.196	–0.006	0.044	0.033
15	0.175	–0.035	–0.014	0.000
16	0.165	–0.013	–0.018	0.034
17	0.162	–0.020	–0.001	–0.007
18	0.138	0.031	0.040	0.047
19	0.109	–0.038	0.005	0.059
20	0.089	–0.009	–0.035	0.016
21	0.095	0.022	0.018	–0.005
22	0.083	0.019	–0.009	0.007
23	0.089	0.016	–0.113	–0.175
24	0.163	0.161	0.306	0.222

may be differenced. Analytically, this issue may be resolved by applying the unit root test, proposed by Dickey and Fuller (1979) for parameter ρ in the auxiliary regression

$$\Delta_1 y_t = \rho\, y_{t-1} + \alpha_1 \Delta_1 y_{t-1} + \varepsilon_t \qquad (3.1)$$

which is derived from the AR(2) model, viz.

$$(1 - \varphi_1 L - \varphi_2 L^2) y_t = \varepsilon_t \qquad (3.2)$$

by expressing the associated autoregressive polynomial in L as

$$1 - \varphi_1 L - \varphi_2 L^2 = (1 - \varphi_1 - \varphi_2)L + (1 - L)(1 - \alpha_1 L) \qquad (3.3)$$

where $\alpha_1 = -\varphi_2$. Using (3.3) in (3.2), we get

$$(1 - L)(1 - \alpha_1 L) y_t = \rho L y_t + \varepsilon_t \qquad (3.4)$$

where $\rho = \varphi_1 + \varphi_2 - 1$. Now, presence of unit root, i.e. $L = 1$ in the autoregressive polynomial implies that the condition for nonstationarity is $1 - \varphi_1 - \varphi_2 = 0$, i.e. $\varphi_1 + \varphi_2 = 1$. Further, region of stationarity is $\varphi_1 + \varphi_2 < 1$. Thus, the unit root test reduces to testing $H_0\!: \rho = 0$ against $H_1\!: \rho < 0$. In the present situation, $\hat{\rho}$ is computed as 0.005. Since calculated value of t-statistic, i.e. 0.212 is found to be greater than the tabulated value of t-statistic at 5% level of significance, i.e. –1.95 (Franses, 1998, Page 82), therefore H_0 is not rejected at 5% level and so $\rho = 0$. Thus, there is presence of one unit root and so differencing is required until the acf shows an interpretable pattern with only a few significant autocorrelations. On taking the first difference of the original series, it is seen that only a few autocorrelations, reported in Table 1, are high making it easier to select the order of the model. On differencing the original series twice, it is seen that the sum of the autocorrelations of double differenced series is –0.507, which implies that the series is overdifferenced (Franses, 1998, Page 50). This suggests that only one differencing would be more appropriate.

The appropriate ARIMA model is chosen on the basis of minimum Akaike information criterion (AIC) and Bayesian information criterion (BIC) values. Using eqs. (2.8) and (2.9), the AIC and BIC values, which are respectively computed as 521.29 and 532.95, the ARIMA(1, 1, 1) model is selected for modelling and forecasting of India's spices export data. The estimates of parameters of above model are reported in Table 2.

Further, the residual error variance for the fitted ARIMA model is computed as 867.762. The graph

Table 2. Estimates of parameters along with their standard errors for fitted ARIMA(1, 1, 1) model

Parameter	Estimate	Standard error
AR1	–0.100	0.159
MA1	0.696	0.119
Constant	1.468	0.966

of fitted model along with data points is exhibited in Fig. 2. Evidently, the fitted ARIMA(1, 1, 1) model is not able to capture successfully the volatility present at various time-epochs, like October 2001; May 2002; March 2004; and March 2006.

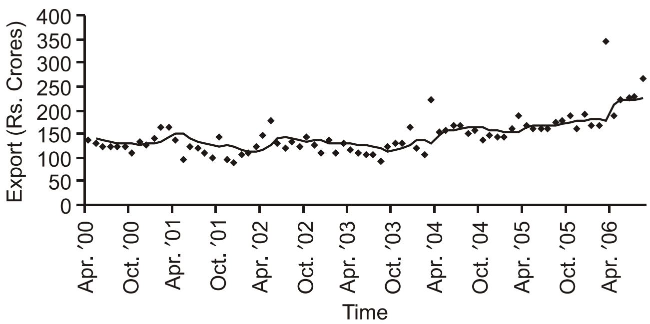

Fig. 2. Fitted ARIMA(1, 1, 1) model along with data points

3.2 Fitting of GARCH Model

On investigating autocorrelations of squared residuals of the fitted ARIMA(1,1,1) model, reported in Table 3, it is found that the autocorrelation is highest at lag 24, which is 0.265. The ARCH-LM test statistic at lag 24 computed using equations (2.12) and (2.13) is 37.48, which is significant at 5% level. But it is not reasonable to apply ARCH model of order 24 in view of the enormously large number of parameters. Therefore, the parsimonious GARCH model is applied. The AR(1)-GARCH(1, 1) model is selected on the basis of minimum AIC and BIC values. The estimates of parameters of the above model along with their corresponding standard errors in brackets ( ) using Method of maximum likelihood with Gaussian distributed error terms are

$$y_t = 157.99 + 0.829\, y_{t-1} + \varepsilon_t$$
$$(33.692)\quad(0.087)$$

where $\varepsilon_t = h_t^{1/2}\eta_t$, and h_t satisfies the variance equation

$$h_t = 1427.855 + 0.354\, \varepsilon_{t-1}^2 + 0.509\, h_{t-1}$$
$$(237.058)\quad(0.277)\quad(0.206)$$

Using eqs. (2.10) and (2.11), the AIC and BIC values for fitted AR(1)- GARCH(1,1) model are respectively computed as 479.77 and 521.97.

Table 3. Sample autocorrelation functions (acf) and partial autocorrelation functions (pacf) of the squared residuals of the ARIMA (1, 1, 1) series

Lag	acf of the squared residuals series	pacf of the squared residuals series
1	–0.015	–0.015
2	–0.045	–0.045
3	–0.030	–0.031
4	–0.041	–0.044
5	0.009	0.005
6	–0.023	–0.027
7	–0.007	–0.010
8	–0.022	–0.027
9	–0.025	–0.027
10	–0.025	–0.031
11	–0.029	–0.035
12	0.028	0.020
13	–0.021	–0.028
14	–0.023	–0.028
15	–0.014	–0.020
16	–0.029	–0.035
17	–0.005	–0.016
18	–0.030	–0.039
19	–0.015	–0.026
20	–0.021	–0.033
21	–0.024	–0.035
22	–0.001	–0.015
23	–0.022	–0.034
24	0.265	0.254

To study the appropriateness of fitted GARCH model, autocorrelation functions of standardized residuals and squared standardized residuals are computed and the same are reported in Table 4. It is found that, in both situations, the autocorrelation functions are insignificant at 5% level, thereby confirming that the mean and variance equations are correctly specified. Conditional standard deviation for

Table 4. Autocorrelation functions of the standardized residuals and squared standardized residuals for fitted GARCH(1,1) model

Lag	acf of standardized residuals	Q-Statistic	Probability	acf of squared standardized residuals	Q-Statistic	Probability
1	–0.093	0.672	---	0.157	1.906	---
2	0.017	0.694	0.405	–0.009	1.913	0.167
3	0.222	4.589	0.101	0.018	1.937	0.380
4	–0.014	4.604	0.203	–0.113	2.957	0.398
5	–0.014	4.621	0.328	–0.041	3.093	0.542
6	0.083	5.192	0.393	0.152	4.995	0.416
7	0.138	6.784	0.341	0.092	5.707	0.457
8	0.009	6.791	0.451	–0.050	5.924	0.549
9	–0.030	6.867	0.551	–0.069	6.336	0.610
10	–0.025	6.922	0.645	–0.135	7.927	0.541
11	0.064	7.288	0.698	–0.109	8.995	0.533
12	0.019	7.321	0.773	0.048	9.202	0.603
13	–0.002	7.321	0.836	0.009	9.210	0.685
14	0.218	11.784	0.545	–0.054	9.482	0.736
15	0.052	12.039	0.603	–0.028	9.558	0.794
16	0.021	12.084	0.673	–0.127	11.116	0.744

fitted model is plotted in Fig. 3. Further, graph of fitted model along with data points is exhibited in Fig. 4. Obviously, the fitted GARCH model is able to capture the volatility present in the data set.

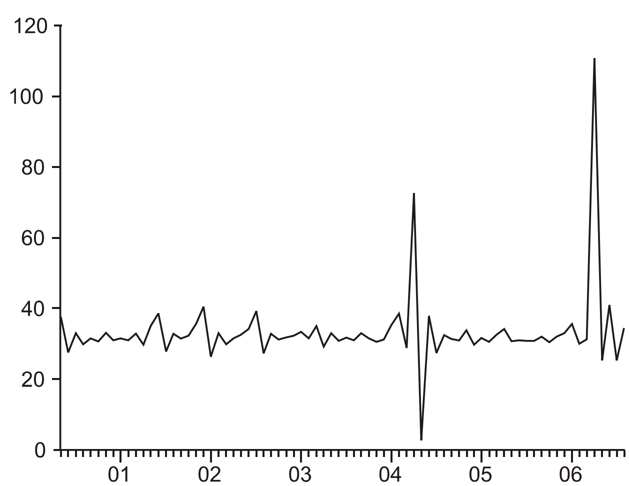

Fig. 3 Conditional standard deviation of fitted AR(1)-GARCH(1,1) model

4. FORECASTING OF INDIA'S SPICES EXPORT DATA

One-step ahead forecasts of export of spices along with their corresponding standard errors inside the brackets ( ) for the months of September 2006 to November 2006 in respect of above fitted models are reported in Table 5. In view of the assumption of homoscedasticity of error terms in ARIMA approach, the one-step ahead forecast error variance remains constant. A perusal indicates that, for fitted GARCH model, all the observed values lie within one standard error of their forecasts. However, this attractive feature

Table 5. One-step ahead forecasts of export of spices (in Rs. Crores) for fitted models

Months	Observed values	Forecasts by	
		ARIMA (1, 1, 1)	AR(1)-GARCH (1, 1)
Sep. '06	270.91	235.67 (29.61)	247.14 (40.93)
Oct. '06	232.59	240.27 (29.61)	231.89 (48.17)
Nov. '06	286.21	241.50 (29.61)	265.68 (33.31)

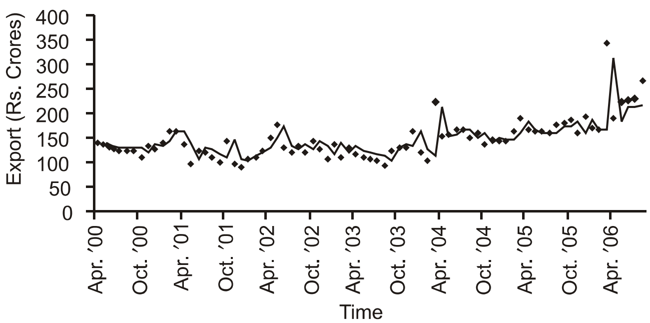

Fig. 4 Fitted AR(1) – GARCH (1,1) model along with data points

does not hold for fitted ARIMA model. Further, for GARCH model, it may be noted that the magnitude of one-step ahead forecast error at a time-epoch is also reflected in the magnitude of corresponding forecast error variance at next time-epoch. For example, when one-step ahead forecast error (i.e. 23.77, being the difference of observed value 270.91 and forecast value 247.14) and corresponding forecast error variance during September 2006 (i.e. 40.93) are large, one-step ahead forecast error variance for October 2006 (i.e. 48.17) is also large. But when one-step ahead forecast error during October 2006 (i.e. 0.70, being the difference of observed value 232.59 and forecast value 231.89) is small, corresponding forecast error variance for November 2006 (i.e. 33.31) is also relatively small. It may be noticed that while periods of strong turbulence caused large fluctuations in Indian spices export, these were often followed by relative calm and slight fluctuations. Further, while most volatility is embedded in the random error, its variance depends on previously realized random errors with large errors being followed by large errors and small by small. Thus, the fitted GARCH model is capable of explaining volatility in the underlying phenomenon. This is in contrast to the ARIMA model wherein the random error is assumed to be constant over time.

The Mean square prediction error (MSPE) values and Mean absolute prediction error (MAPE) values for fitted GARCH model are respectively computed as 18.14 and 15.00, which are found to be lower than the corresponding ones for fitted ARIMA model, viz. 33.17 and 29.02 respectively. Further, a comparative study of forecasts of monthly spices export by above discussed two models is carried out on the basis of their Relative mean absolute prediction error (RMAPE) values defined as

$$\text{RMAPE} = \frac{1}{6}\sum_{i=1}^{6}\left\{\left|y_{t+i} - \hat{y}_{t+i}\right| / y_{t+i}\right\} \times 100$$

The RMAPE values for fitted ARIMA (1,1,1) and AR(1)-GARCH(1,1) models are respectively computed as 32.46 and 10.82. The lower values of all the three statistics, viz. MSPE, MAPE, and RMAPE reflect superiority of GARCH approach for forecasting purposes also.

The more realistic forecast intervals for India's spices export data obtained through GARCH approach could be of immense help to planners in formulating appropriate strategies. This type of information would go a long way in arriving at the appropriate decisions on several issues, like Quantities of spices in future to be exported and quantities to be earmarked for domestic consumption, Whether to impose ban on exports at various points of time, and Whether or not to impose export duty and how much in case export of spices is allowed. This would enable the planners to take appropriate policy decisions from time to time well in advance in order to meet the targets set for Indian spices export. These, in turn, would also benefit the farmers in production of optimum quantities of spices. All this would ultimately result in efficient management of India's spices sector export scenario on a sound statistical basis.

5. CONCLUDING REMARKS

It has been shown that for Indian spices export time-series data, the usual assumption of homoscedasticity of error terms is not satisfied. For modelling as well as forecasting of this data, the GARCH nonlinear time-series model has performed better than the well-known Box-Jenkins ARIMA model. Therefore, for data sets exhibiting volatility, ARIMA approach should be abandoned in favour of GARCH methodology in order to obtain more accurate forecasts and changing forecast interval lengths. The methodology advocated in this paper can also be used for forecasting other volatile data sets.

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