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An Empirical Investigation of Arima and Garch Models in Agricultural Price Forecasting

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Abstract

The present study deals with time series models which are non-structural-mechanical in nature. The Box Jenkins Autoregressive integrated moving average (ARIMA) and Generalized autoregressive conditional heteroscedastic (GARCH) models are studied and applied for modeling and forecasting of spot prices of Gram at Delhi market. Augmented Dickey Fuller (ADF) test is used for testing the stationarity of the series. ARCH-LM test is used for testing the volatility. It is found that ARIMA model cannot capture the volatility present in the data set whereas GARCH model has successfully captured the volatility. Root Mean square error (RMSE), Mean absolute error (MAE) and Mean absolute prediction error (MAPE) were computed. The GARCH (1,1) was found to be a better model in forecasting spot price of Gram. The values for RMSE, MAE and MAPE obtained were smaller than those in ARIMA (0,1,1) model. The AIC and SIC values from GARCH model were smaller than that from ARIMA model. Therefore, it shows that GARCH is a better model than ARIMA for estimating daily price of Gram.

Keywords: ARIMA model, Forecasting, GARCH model, Gram Price, Stationarity, Unit root test.

Introduction

Indian agriculture is characterized by risks and uncertainties in the production and high volatility in the prices of agricultural commodities. Most often, in spite of good production, farmers are making loss due to low prices. In the same way, many times the consumers are paying exorbitant prices. Price forecast is one of the critical inputs to the farmers to take the production and marketing decisions and to the policy makers for administering commodity proGrams and assessing market impacts of domestic or international events. Monitoring commodity price can play a major role on the overall macroeconomic performance of a country. Therefore, the commodity price forecast is a key input to macroeconomic policy planning and formulation.

The literature on price forecasting is based on two main groups of linear, single-equation, reduced-form econometric models as well as Time Series models. The first group includes models which are based on the market efficiency hypothesis, while models belonging to the second group consider the effects of commodity market and other variables on commodity prices. Studies have compared the different models for forecasting of prices, production and export. Autoregressive integrated moving average (ARIMA) models performed better than the structural model in predicting the wheat price (Moghaddasiand *et al.*,2008) and it was found appropriate for forecasting oil palm prices (Nochai *et al.*, 2006). The efficiency of ARIMA and generalized autoregressive conditional heteroskedasticity (GARCH) models were compared for modeling and forecasting of India's volatile spices export (Paul *et al.*, 2009) and ARIMA model was employed for forecasting of inland fish production in India (Paul and Das, 2010).

This study is undertaken with the hypothesis that ARIMA model for forecasting is suitable for non-volatile data, as its inability to capture the volatility component more precisely. Whereas GARCH models are more versatile in capturing the persistent volatility in the time series data. The prices of pulse (Gram) commodities are more volatile than cereal commodities in India as evident from the time series data. Therefore, in the present study, univariate ARIMA and GARCH models were fitted to identify better forecast for prices of Gram. To this end, the forecast performance was compared on the basis of Mean square prediction error (MAPE), mean absolute prediction error (MAE) and Root mean square errors (RMSE).

Data and Methodology

The study has been illustrated with the time series data on spot price of Gram in Delhi Market from 01 January 2007 to 19 April 2012 procured from NCDEX website. The last 60 observations were used for validation of the models and hence were not been considered for model building. The methodologies were employed to test the time series properties of the data, to identify and fit the models and checking the models with time series data.

Testing Stationarity

The time series properties of Gram prices were assessed by performing unit root test. The most widely used tests for testing the unit root or non-stationary of time series are Dickey and Fuller (DF) test (1979) and the Augmented Dickey Fuller (ADF) test. DF test is as follows:

$$Y_t = \mu \ + \rho Y_{t-1} + e_t \qquad \ldots(1)$$

Where, Y_t = spot price (response or dependent) variable at time t, μ and ρ are parameters and e_t is random term. Here the null hypothesis is that H_0: ρ = 1 indicating that the series is non-stationary.

$$\Delta Y_t = \mu + \gamma Y_{t-1} + e_t \qquad \ldots(2)$$

Where $\gamma = \rho - 1$ & $\Delta Y_t = Y_t - Y_{t-1}$

The null hypothesis is $H_0 : \gamma = 0$. The test can be carried out by performing a τ-test on the estimated γ. The τ- statistics under the null hypothesis of a unit root does not follow the conventional t- distribution. The test showed that the distribution under null hypothesis is nonstandard and simulated critical values for selected samples size. If the error term e_t is auto-correlated, the equation (2) is modified as

$$\Delta Y_t = \mu + \gamma Y_{t-\circledcirc} + \alpha_i \sum_{i=\circledcirc}^{m} \Delta Y_{t-\circledcirc} + \in_t \qquad \ldots(3)$$

Where m = number of lagged difference terms required so that the error term $\in_t$ is serially independent. The null hypothesis is the same as the DF test, i.e., $H_0 : \gamma = 0$, implying that Y_t is nonstationary. The model like the equation (3) is called Augmented Dickey Fuller. This test was applied to the spot price series of Gram to test the null hypothesis that the series has a unit root or nonstationary. The stationarity of the series was also determined by considering the autocorrelation function (ACF).

Time series models

ARIMA models are capable of representing stationary as well as nonstationary time series (Box *et al.*, 2007). GARCH) model is capable to capture volatility in time series data. Thus, both models were fitted to the Gram prices and their performances were compared.

Non-seasonal Box-Jenkins Models for Stationary Series

The general form of a p^{th} order autoregressive model: AR(p) is:

$$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \ldots + \alpha_p Y_{t-p} + \varepsilon_t \qquad \ldots(4)$$

Where, Y_t = Response (dependent) variable at time t, $\alpha_0, \alpha_1, \alpha_2, \ldots\ldots\ldots, \alpha_p$ = Coefficients to

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be estimated and ε_t = Error term at time t.

The general form of a qth order moving average model: MA(q) is:

$$Y_t = \mu + \varepsilon_t - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - \ldots - \theta_q\varepsilon_{t-q} \qquad \ldots(5)$$

Where, $\mu =$ constant mean of the process, $\theta_1, \theta_2, \ldots\ldots\ldots, \theta_q$ = Coefficients to be estimated, ε_t = error term at time t, $\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots\ldots\ldots, \varepsilon_{t-q}$ = errors.

Now, the general form of ARMA(p,q) is:

$$Y_t = \psi_0 + \psi_1 Y_{t-1} + \psi_2 Y_{t-2} + \ldots + \psi_p Y_{t-p} + \varepsilon_t - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - \ldots - \theta_q\varepsilon_{t-q} \qquad \ldots(6)$$

ARIMA model

Model for non-seasonal series are denoted by ARIMA (p, d, q). Here, p indicates the order of the autoregressive part, d indicates the order of differencing, and q indicates the order of the moving average part. If the original series is stationary, d = 0 and the ARIMA models reduce to the ARMA models. A highly useful operator in time-series theory is the lag or backward linear operator (B) defined as: $BY_t = Y_{t-1}$.

The difference linear operator (Δ), defined as: $\Delta Y_t = Y_t - Y_{t-1} = Y_t - BY_t = (1-B)Y_t$

The stationary series Wt obtained as the dth difference (Δ^d) of Y_t

$$W_t = \Delta^d Y_t = (1-B)^d Y_t \qquad \ldots(7)$$

ARIMA(p,d,q) has the general form:

$$\psi_p(B)(1-B)^d Y_t = \mu + \theta_q(B)\varepsilon_t \quad \text{or} \quad \psi_p(B)W_t = \mu + \theta_q(B)\varepsilon_t \qquad \ldots(8)$$

Model must be checked for adequacy by considering the properties of the residuals. The residuals from ARIMA model must have the normal distribution and should be random. An overall check of model adequacy is provided by the Ljung-Box Q statistic. The test statistic Q is as follows:

$$Q_m = n(n+2)\sum_{k=1}^{m}\frac{r_k^2(e)}{n-k} \sim X^2_{m-r} \qquad \ldots(9)$$

Where, $r^2_k(e)$ = the residual autocorrelation at lag k, n= the number of residuals, m= the number of time lags includes in the test. If the p-value associated with the Q statistic is small (p-value $< \alpha$), the model is considered inadequate.

GARCH Model

Autoregressive conditional heteroskedastic (ARCH) models are used whenever there is reason to believe that, at any point in a series, the terms will have a characteristic size, or variance. In particular ARCH models assume the variance of the current error term to be a function of the actual sizes of the previous time periods' error terms. Often, the variance is related to the squares of the previous innovations. ARCH models are generally employed in modeling financial time series that exhibit time-varying volatility clustering. If an ARMA model is assumed for the error variance, the model is called a generalized autoregressive conditional heteroskedasticity (GARCH) model (Bollerslev, 1986).

To measure the extent of price volatility, GARCH (1, 1) model is specified as**:**

$$Y_t = X_t^{'}\theta + \epsilon_t \qquad \ldots(10)$$

$$Y_t = \omega + \alpha\,\epsilon_{t-1}^2 + \beta\,\sigma_{t-1}^2 \qquad \ldots(11)$$

σ_t^2 is the conditional variance. This model is also consistent with the volatility clustering often seen in financial returns data.

There are two equivalent representations of the equation (11) that are useful for interpreting the model. The first representation: if we recursively substitute for the lagged variance on the right hand side of equation (11), then conditional variance can be expressed as a weighted average of the lagged squared residuals as:

$$\sigma_t^2 = \frac{\omega}{(1-\beta)} + \alpha \sum_{j=1}^{\infty} \beta^{j-1}\ \epsilon_{t-j}^2 \qquad \ldots(12)$$

This can be noted that the GARCH (1, 1) variance specification is analogous to the sample variance, but it down-weights more distant lagged squared errors.

The second representation: the error in the squared returns is given by $v_t = \epsilon_t^2 - \sigma_t^2$. Substituting for the variance in the variance equation and rearranging the terms, the model can be written in terms of the errors as:

$$\epsilon_t^2 = \omega + (\alpha+\beta)\epsilon_{t-1}^2 + v_t - \beta\, v_{t-1} \qquad \ldots(13)$$

Thus, the squared error follows a hetroscedastic ARMA (1, 1) process. The ARCH parameters corresponds to α and GARCH parameters to β. If the sum of ARCH and GARCH coefficients close to 1, it indicates that volatility is quite persistent in the price series of Gram.

For testing the ARCH effect, let ε_t be the residual series. The squared residual $\left\{ \mathring{a}_t^2 \right\}$ is then used to check for conditional heteroscedasticity, which is also known as the ARCH effect. To this end, two tests, briefly discussed below, are available. The first one is to apply the usual Ljung-Box statistic *Q(m)* (Equation 9) to the $\left\{ \mathring{a}_t^2 \right\}$ series. The null hypothesis is: first *m* lags of autocorrelation functions of the $\left\{ \mathring{a}_t^2 \right\}$ series are zero. The second test for conditional heteroscedasticity is the LM test, which is equivalent to usual *F*-statistic for testing $H_0\colon a_i = 0$, $i = 1, 2, \ldots, q$ in the linear regression

$$\mathring{a}_t^2 = a_0 + a_1\, \mathring{a}_{t-1}^2 + \ldots + a_q\, \mathring{a}_{t-q}^2 + e_t,\ t = q+1, \ldots, T \tag{14}$$

where e_t denotes error term, q is prespecified positive integer, and T is sample size. Let $SSR_0 = \sum_{t=q+1}^{T} \left(\mathring{a}_t^2 - \bar{u} \right)^2$, where $\bar{u} = \sum_{t=a+1}^{T} \mathring{a}_t^2 / T$ is sample mean of $\left\{ \mathring{a}_t^2 \right\}$, and $SSR_1 = \sum_{t=q+1}^{T} \hat{e}_t^2$, where $\hat{e}_t$ is least squares residual of (14). Then, under H_0:

$F = \dfrac{(SSR_0 - SSR_1)/q}{SSR_1 (T - q - 1)}$, is asymptotically distributed as chi-squared distribution with q degrees of freedom. The decision rule is to reject H_0 if $F > \div_q^2(\acute{a})$, where $\div_q^2(\acute{a})$ is the upper $100(1-\acute{a})^{th}$ percentile of $\div_q^2$ or, alternatively, the *p*-value of *F* is less than $\acute{a}$.

Diagnostic measures for evaluation of forecast performance

The Bayesian information criterion (BIC) or Schwarz information criterion (SIC) is used for model selection among a finite set of models. It is based, in part, on the likelihood function, and it is closely related to Akaike information criterion (AIC). In model building, it is possible to increase the likelihood by adding parameters, but doing so, it may result in over fitting. The BIC resolves this problem by introducing a penalty term for the number of parameters in the model.

Let: n = number of observations, k = number of parameters to be estimated, L_{max} = the maximized value of the log-Likelihood for the estimated model. Then, SIC and AIC are:

$$SIC = \ln[n]k - 2\ln[L_{max}]$$

$$AIC = \left[\frac{2n}{n-k-1}\right]k - 2\ln[L_{max}]$$

and , HQIC (Hannan-Quinn information criterion) $= 2ln[ln[n]]k - 2ln\ [L_{max}]$

The best model was selected with the lowest value of information criterion.

For measuring the accuracy in fitted models, Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Relative Mean Absolute Prediction Error (RMAPE) were computed by using the formulae given below. Validations of forecasts were done in different forecast horizons viz. 5, 10, 15, 20, 30, 40, 50 and 60 observations. The MAE, MAPE and RMAPE formulae are:

$$\text{MAE} = 1/h\sum_h \left|y_{t+h} - \hat{y}_{t+h}\right|$$

$$\text{MAPE} = 1/h\sum_h \left|y_{t+h} - \hat{y}_{t+h}\right|$$

$$\text{RMAPE} = 1/h\sum_h \left\{\left|y_{t+h} - \hat{y}_{t+h}\right| / y_{t+h}\right\}\times 100$$

Results and Discussion

Augmented Dickey Fuller test was applied to the Gram spot price series to test the null hypothesis that the series has unit root or nonstationary. The results are given in Table 1. The result shows that the series has unit root. The alternative hypothesis is true. Thus, data series was subjected to first differencing to make the data stationary. The results of differenced series indicated that the ‘τ -Statistic’ obtained for price series is not significant, we are bound to reject the null hypothesis and the alternative hypothesis of stationary series is true. The Gram price series became stationary at one differencing and the data is now ready for further econometric analysis.

Table-1. Augmented Dickey Fuller Test for Spot Market Price Delhi Market

	Level Data		At First Difference	
	t-Statistic	Prob.*	t-Statistic	Prob.*
ADF Test value	-1.787	0.7108	-25.524	<0.001
1% level	-3.963		-3.963	
5% level	-3.412		-3.412	
10% level	-3.128		-3.128	

Estimation of ARIMA model

Estimated parameters for a tentative model were selected on the basis of significance level of AR and MA terms given in Table 2. In this particular case only one moving average term was found to be statistically significant. The estimates equation obtained in the model as follows:

$$\psi_p(B)W_t = 0.629 + 0.112(B)\varepsilon_t$$

ARCH Lagrange Multiplier (LM) test, a heteroscedastic test developed by Engle (1982), was used to determine the presence of ARCH effect in the residuals.

Table-2. Parameter Estimates of ARIMA (0,0,1) model for Spot Price of Gram in Delhi Market

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.629	1.039	0.604	0.545
MA(1)	0.112	0.024	4.499	0
Log likelihood	-7963.11	Akaike info criterion		10.069
F-statistic	18.739	Schwarz criterion		10.076
Prob(F-statistic)	0.000016	Hannan-Quinn criter		10.072
Inverted MA Roots	-0.11	Durbin-Watson stat		2.006

Estimation GARCH Model

In results of the conditional mean equation are presented in Table 3. The parameters were found to be as ω (0.510) and statistically significant MA term (0.136). The conditional variance equation gave ω = 17.464, $\alpha_{1=}$0.095 and β_1 = 0.895. A high value of β_1 implied that, volatility was persistent and it took a long time to change.

Table-3. Parameter Estimates of GARCH (1, 1) model for Spot Price of Gram in Delhi Market

Method: ML - ARCH (Marquardt) - Normal distribution				
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.510	0.895	0.570	0.568
MA(1)	0.136	0.027	4.963	<0.001
Variance Equation				
C	17.464	3.640	4.797	<0.001
RESID(-1)^2	0.095	0.008	10.709	<0.001
GARCH(-1)	0.895	0.007	113.807	<0.001
	Akaike information criterion			9.779
F-statistic	4.464	Schwarz criterion		9.796
Prob(F-statistic)	0.0013	Hannan-Quinn criterion		9.786
Inverted MA Roots	-0.14	Durbin-Watson stat		2.051

The long spikes are the high volatile periods of Gram price series as shown in Figure 1. With GARCH (0, 1) model, the volatility clustering was detected. There were lesser spikes compared to conditional standard deviation graph as given in Figure 2. In diagnostic checking stage, a test for conditional heteroscedasticity in the data with ARCH-LM test on the residuals was also performed. The ARCH-LM test for one lag difference of residuals squared was 0.318 under $\chi2$ (1). But, the null hypothesis was not rejected since the p-value was 0.5721where it had greater than 5% of significance level. On the other hand, f-statistic was 0.318 and the test also not rejected the null hypothesis at the same condition. The ARCH-LM test on the residuals of this model showed that the conditional heteroscedasticity was no longer present in Gram price series. First order difference of residuals Graph GARCH is shown in Figure 3. The occurrence of significant spikes represent the high volatile period. Standardized residuals Graph for GARCH (1, 1) model is given in Figure 4. In Figure 4, a band of lines were joined together around mean zero with little spikes throughout the time series. The plot can be observed to have an uniform mean and a unit variance. The distribution of the standardized residuals was summarized in the histogram and normality test as in Figure 5. The figure shows that the residuals were evenly distributed. The mean value was equal to 0.018, and the standard deviation is 1.0003 which implies that the standardized residuals were normally distributed. The skewness and kurtosis values were 0.370 and 5.479, respectively. The distribution is a bit positively skewed and fat tailed. The Jarque- Bera test revealed that the standardized residual was normally distributed.

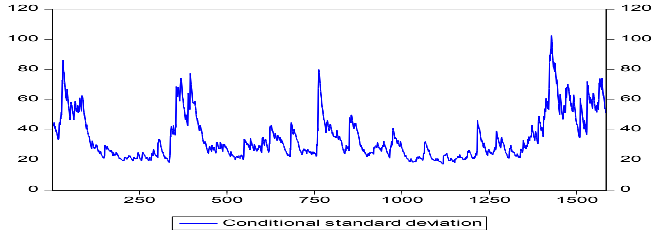

Fig-1. Conditional standard deviation for GARCH (1,1) model

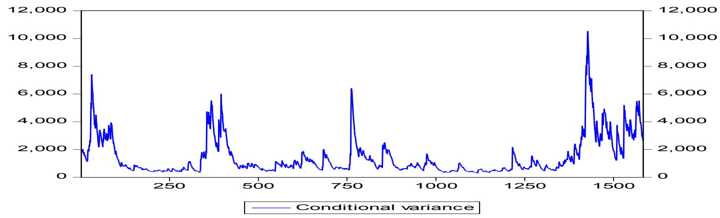

Fig-2. Conditional variance for GARCH (1,1) model

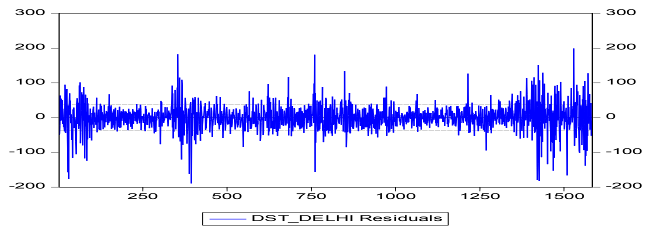

Fig-3. First order difference of residuals Graph GARCH

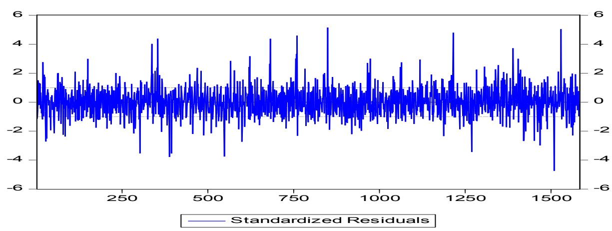

Fig-4. Standardized residuals Graph for GARCH(1,1) model

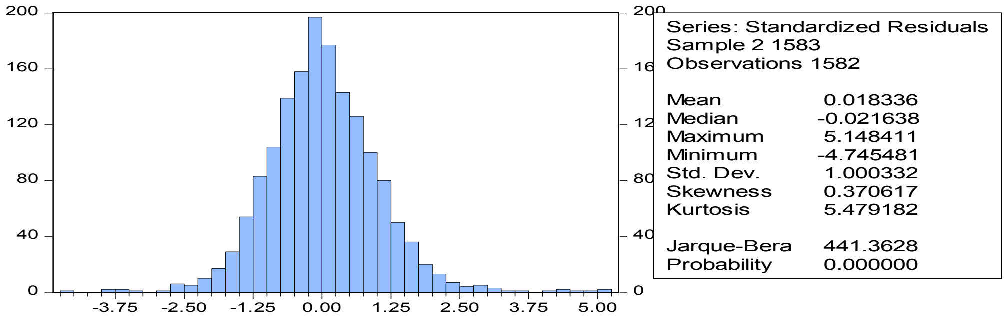

Fig-5. HistoGram Normality Test of first order difference Gram Price series

Evaluation of forecast performances of ARIMA and GARCH models

The AIC and SIC values were obtained from estimated equations for both ARIMA and GARCH models presented in Table 4. Both the AIC and SIC values from GARCH model were smaller than that of ARIMA model. Therefore, it is concluded that GARCH model performed better than ARIMA for modeling and forecasting of daily prices of Gram. Forecast error becomes less if. actual values and forecast values are closer. Thus, smaller RMSE, MAE and MAPE values are preferred. Therefore, MAE, MAPE and RMAPE values were calculated for fitted ARIMA and GARCH models at different forecast horizons (Table 5). All forecast errors from GARCH model were found to be smaller than that of ARIMA model. Further, daily spot prices (₹ per 10 kg) of Gram were forecasted using both the models and the results for last 30 observations were compared with actual prices. ARIMA model forecasts were lower than actual prices for all the 30 cases and decrease in forecast means prices over actual prices for first 15 and last 15 days by nearly 11 and 10 percent, respectively. On the other hand, forecasted prices by GARCH model were more for 17 and less for 13 cases and deviation were not significant. In Nutshell, it is concluded that GARCH model performed better than ARIMA model in case of volatile data. In other words, GARCH model is a better model for predicting daily prices of Gram.

Table 4 : Information criterion for ARIMA and GARCH models

Model	AIC	SIC
ARIMA	10.06004	10.07023
GARCH	9.779861	9.796822

Table 5. Forecast Performance of ARIMA and GARCH models

Forecast Days	MAE		MAPE		RMSE	
	ARIMA	GARCH	ARIMA	GARCH	ARIMA	GARCH
5	14.724	14.862	0.441	0.445	19.275	19.471
10	45.239	41.964	1.282	1.189	73.198	71.996
15	42.671	40.095	1.203	1.132	64.384	63.278
20	46.023	44.548	1.273	1.235	63.746	63.046
30	46.189	46.009	1.286	1.269	61.230	60.768
45	50.770	50.220	1.411	1.387	64.661	64.316
60	48.544	48.290	1.359	1.345	62.004	61.868

Table 6. Gram spot price (₹ per 10 kg) forecast for last 30 observations using ARIMA and GARCH models

Observations	Actual Prices	ARIMA Forecast		GARCH Forecast	
		Prices	Change over actual (%)	Prices	Change over actual (%)
1	775.0	712.7	-8.04	803.1	3.63
2	770.0	712.8	-7.43	803.4	4.34
3	775.0	713.0	-8.00	803.6	3.69
4	780.0	713.2	-8.56	803.9	3.06
5	789.5	713.4	-9.64	804.1	1.85
6	800.0	713.6	-10.80	804.3	0.54
7	805.0	713.8	-11.33	804.6	-0.05
8	827.5	713.9	-13.73	804.8	-2.74
9	826.3	714.1	-13.58	805.1	-2.57
10	830.0	714.3	-13.94	805.3	-2.98
11	828.0	714.5	-13.71	805.6	-2.71
12	825.0	714.7	-13.37	805.8	-2.33
13	821.3	714.9	-12.96	806.0	-1.86
14	820.0	715.0	-12.80	806.3	-1.67
15	810.0	715.2	-11.70	806.5	-0.43
16	810.0	715.4	-11.68	806.8	-0.40

Contd.

17	820.0	715.6	-12.73	807.0	-1.59
18	825.0	715.8	-13.24	807.3	-2.15
19	820.0	716.0	-12.68	807.5	-1.52
20	806.3	716.1	-11.19	807.7	0.17
21	806.0	716.3	-11.13	808.0	0.25
22	806.0	716.5	-11.10	808.2	0.27
23	800.0	716.7	-10.41	808.5	1.06
24	800.0	716.9	-10.39	808.7	1.09
25	790.0	717.1	-9.23	809.0	2.41
26	780.0	717.2	-8.05	809.2	3.74
27	770.0	717.4	-6.83	809.4	5.12
28	762.5	717.6	-5.89	809.7	6.19
29	755.0	717.8	-4.93	809.9	7.27
30	760.0	718.0	-5.53	810.2	6.61
Average (first 15 observations)	805.5	713.9	-11.37	804.8	-0.09
Average (last 15 observations)	794.1	716.7	-9.75	808.5	1.81
Forecast prices less (more) than actual (No.)		30 (0)	-	13(17)	-

Conclusion

ARIMA model was applied for forecasting Gram prices and model gives reasonable and acceptable forecasts. But, it did not perform very well when there exist volatility in the data series. GARCH model was also fitted to forecast Gram prices. The GARCH model performs better on account of its ability to capture the volatility by the time varying conditional variance. The GARCH was found to be a better model than ARIMA in forecasting spot price of Gram because the values for RMSE, MAE and MAPE calculated using GARCH model were lesser than ARIMA model. AIC and SIC values were also lower in GARCH model than that from ARIMA model. The deviations between actual and forecasted Gram prices were little in GARCH model. Therefore, it is suggested that GARCH model is a better model than ARIMA for forecasting volatile prices.

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