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Forecast of Agricultural Commodity Price in the Presence of Volatility

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ABSTRACT

Modelling and forecasting of the sale price of an agricultural commodity in the presence of volatility is the focus of this work. Effort has been made to build an efficient forecasting model using the observed data on monthly onion prices for the period of January, 2003 to December, 2020. Non-stationarity and volatility are apparent in the price data observed in the commodity market as these prices are influenced by increasing demand, financial crisis, cross-sectional price variability. Considering all the above conditions, it is found that AR(1)-GARCH(1,1) model is suitable for forecasting the volatility present in the observed data set. The forecast of price as well as the conditional variance suggest that the volatility would be apparent and remain constant for upto June 2024. Forecast values of price of onion show a steadily decreasing trend which indicates that the price for a period of 24-months for the season 2023-24 shows some degree of stability. Thus, the onion cultivators of Bolpur market may earn more revenue by selling their produce as early as possible so that they can avoid the extra expense which will incur in storing the same for a long period.

Keywords Conditional variance, Forecasting model, GARCH, Stationarity, Volatility clustering.

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INTRODUCTION

Farmers' choice of crops to be cultivated depends on several factors like its demand, productivity, profitability, marketability and to grow farmers' interest in cultivating any crop, the long-term movement or trend of demand and profit, market condition etc. should be well studied. However, there are commodities where the price of the commodity varies over time and season. This fluctuation is described as volatility in the economic term. In general, high volatility is very apparent in the present financial market, especially in the case of daily market price data of different commodities. The reason behind such volatility can be found in the complications of storability, seasonality, transportation facility, natural calamity, price shocks announcements of price subsidies or trading activities. Volatility modelling is of great interest to most financial analysts and researchers. The problem of price variability modelling mainly focuses on the analysis of patterns in the data and when volatility is present, determination of pattern becomes different. The basic strategy behind the evaluation of price instability would be based on the study of movements and dynamics of price data in the current market environment.

Two basic reasons to study the price volatility in a time series data are the following (i) To study the nature of fluctuations in price leading to non-stationarity which cannot be handled using the differencing techniques or transformations (ii) To predict the time series data with a predetermined level of confidence. It is worth mentioning here that the time points where the magnitude of variance of the time series data changes do not occur randomly across the data, instead, a degree of autocorrelation among those values can be seen. First, it was studied by Mandelbrot (1963) and Black & Cox (1973). Later, Engle & Yoo (1987) developed the modern approach to handle volatility in price data by using autoregressive conditional heteroscedastic (ARCH) model. Then, this ARCH model was further generalized by Bollerslev (1987) and named as generalized autoregressive conditional heteroscedastic (GARCH) model. GARCH models assume the time varying conditional variance in the response variable. The GARCH models developed by Bollerslev have been found to have significant predictive power when it deals with the intra-day data (Val *et al.* 2014). In the present work modelling and forecasting the onion price under the presence of price volatility using GARCH model has been considered. For that purpose, the data on minimum price for onion from the Directorate of Marketing & Inspection (DMI) has been used. The data set comprises of monthly average price of onion from January 2003 to December 2020 for Bolpur market, West Bengal. The primary focus of this study is to fit an appropriate model from the GARCH family that can capture the volatility present in the data and can predict the onion's future prices. Keeping this objective in mind, the paper specifically investigates the following research questions:

How good the AR-GARCH model is for predicting the onion price observed at Bolpur market in comparison to other models.

Is it beneficial to use the output of the model selected for hedging against risks by the onion producers?

MATERIALS AND METHODS

In the present study the time series data contains 234 observations on average monthly price of onion for the period of January, 2003 to June, 2022. These data points are recorded for Bolpur market of West Bengal.

ARIMA model specification

A time series forecasting model works nicely for the purpose of prediction if the series is stationary. Stationary times series should be used in ARMA (*p, q*) or ARIMA (*p, d, q*) models. If it is not stationary, then it should be adjusted by taking difference of the actual series. First difference value, in terms of backshift operator (*B*) can be written as, $Y_{t-1} = BY_t$.

For "*p*" AR components, "*q*" MA components and "d " number of differences taken to make the series stationary, the ARIMA (*p, d, q*) model can be expressed in the form of (1) (Nath & Bhattacharya 2022).

$$(1-\sum_{j=1}^{p} \phi_j B^j)\,(1-B)^d Y_t + (1+\sum_{i=1}^{q} \theta_i B^i)\,\varepsilon_t, \qquad (1)$$

Where, ϕ_j = the coefficient of AR process at lag *j*, θ_i = the coefficient of MA component at lag i, B = The backshift operator, Y_t = the actual value of the series at time *t*, ε_t = White noise error at time *t*.

Test for stationarity

In literature, basically, three tests viz., Augmented Dickey Fuller (ADF), Kwiatkowski, Phillips, Schmidt and Shin (KPSS) and Phillips Perron (PP) are widely used for testing the stationarity or presence of unit root in time series. In the present work, KPSS and PP tests have been considered for the same, simultaneously which are given below:

Kwiatkowski, Phillips, Schmidt and Shin (KPSS) test

Taking the null hypothesis (H_0) as a stationary process and the unit root as an alternative (H_1) is in accordance with a conservative testing strategy. If we then reject the null hypothesis, we can be confident that the series indeed has a unit root. Therefore, if the results of the tests above indicate a unit root but the result of the KPSS test indicates a stationary process, one should be cautious and opt for the latter result $H_0 : \sigma^2 = 0$.

Under the H_0 of $e_t \sim$ NIID $(0, \sigma^2)$" , the test statistic is defined in (2).

$$LM = \frac{(\sum_{t=1}^{T} S_t^2)}{\sigma_e^2} \quad (2)$$

Where $\hat{\sigma}_e^2 = \frac{\sum_{t=1}^{T} e_t^2 S_t}{T} = \sum_{i=1}^{t} e_i$, $t = 1.......T$ and e_t are the residuals from the regression of y_t on a time trend (*t*).

Phillips perron (PP) test

The phillips perron test is a unit root test. Kwiatkowski *et al.* (1992) reported that the PP test performs worse in finite samples than the ADF test and the advantage of the PP test is that it is nonparametric test, i.e., it does not require to select the level of serial correlation as in ADF. It rather takes the same estimation scheme as in ADF test but corrects the statistic to conduct for autocorrelations and heteroscedasticity (Phillips & Perron (1988).

Test for presence of ARCH effect

To test the presence of heteroscedasticity we need the residuals, which can be obtained by means of an appropriate ARIMA (*p, d, q*) model. Under this test, H_0: heteroscedasticity is not present against H_1: heteroscedasticity is present, have been considered. The test statistic has been taken as, "ARCH-LM = $nR^2 \sim \chi^2_{(p)}$, where n is the sample size and R^2 is the coefficient of determination obtained by squared residuals regressed on constant and its lagged values up to order *p*, as given in (3). The decision rule is that, reject H_0, if the observed value of the statistic is more than the critical $\chi^2_{(p)}$ value, otherwise do not reject.

$$e_t^2 = \delta_0 + \sum_{i=1}^{p} \delta_i e_{t-i}^2 + v_t, \quad (3)$$

Where, e_t^2 = squared residual at time *t*, δ_i = parameter estimates of regression model, v_t = error term.

Test for the normality of residuals

The test for normality of the residuals has been performed by using normal Q-Q plot (Nath *et al.* 2020).

ARCH and GARCH model specifications

Let, y_t be the onion price at time *t*, then the price (y_t) can be modelled as, $y_t = \mu_t + \varepsilon_t$, where μ_t can be obtained by using (1).

Now, $\varepsilon_t = y_t - \mu_t$,

Let, ε_t be modelled by using" GARCH *(p, q)*.

Here, $\varepsilon_t = \sqrt{h_t \eta_t}$ and $(\sqrt{(h_t)})^2 = h_t = \omega + \sum_{i=1}^{q} \alpha_t \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j (\sqrt{(h_{t-j})})^2$, where $\eta_t \sim i.i.d\ (0,1)$.

or it can be written as, $h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j}$. (4)

Where, "ω (intercept) > 0; $\alpha_i \geq 0$ for i = 1,2,…,*q*, $\beta_j \geq 0$ for j =1, 2,…,*p*, h_t = conditional variance, $\sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2$ = ARCH effect and $\sum_{j=1}^{p} \beta_j (\sqrt{h_{t-j}})^2$ = GARCH effect. If $\sum_i \alpha_i + \sum_j \beta_j < 1$, then the specified GARCH (*p, q*) model is covariance stationary, otherwise non-stationary.

In this notation α_i and β_j are the parameters of GARCH model. It is to be noted that if h_t is ARMA, then $\sqrt{(h_t)}$ is GARCH. The model given in (4) is the generalized version of ARCH model proposed by Engle & Yoo (1987) and known as a generalized autoregressive conditionally heteroscedastic (GARCH) model developed by Bollerslev (1987).

Here we have studied the problem of time varying residual variance which is present in the observed data with the help of ARCH (*q*) and GARCH (*p, q*) models. The GARCH model, which is an extended version of the ARCH model that takes care of the inclusion of lags of conditional variances, is used to capture the conditional variance present in the model.

Model fitting and selection criteria

First, the two orders, i.e., *p* and *q* of GARCH (*p, q*) model are to be decided for fitting a GARCH model.

In this case, the ACF and PACF plots of the original and squared series of the obtained residuals are to be examined thoroughly. The values of *p* and *q* orders for building a candidate model can be decided in a similar way, as it is done in ARMA (*p, q*) model fitting. The following point is to be considered while deciding the possible orders of the candidate models:

If the original series of residuals is found to be white noise, then the series of squared residuals needs to be examined and the values of *p* and *q* of the GARCH model are then decided by looking at ACF and PACF plot of the squared residuals series.

One among the four model selection criteria viz., AIC, BIC, Shibata, and Hannan-Quinn can be used for selecting the best fit model. However, all these criteria, simultaneously have been considered for the selection of GARCH models and the selected models are then cross validated by using validation data set in the form of absolute percentage error (APE) and mean absolute percentage error (MAPE).

RESULTS AND DISCUSSION

The whole data set (234 observations) is divided into two parts viz., training and validation sets. The training set has 214 observations and the remaining 20 observations have been kept for cross validation of the fitted models under the validation data set. Models were built by using training data set and cross validated by using validation data set. To check the presence of ARCH effect, all the data points have been used. The accuracy of the fitted models has been checked by obtaining the variation between forecast and actual values. The extent of these variations is determined by means of APE and MAPE.

Model fitting

Data on average monthly price of onion for Bolpur market are used for forecasting the price for future time points. In this case, the ARIMA models are fitted to obtain the residuals and these residuals are then tested for possible presence of ARCH effect. The stationarity of the actual series is tested by using KPSS and PP tests. In the case of actual series, the KPSS and PP test statistics are found to be significant indicating the non-stationarity of the actual series. So, the first seasonal difference of the actual series is obtained and tested. It is observed that the differenced series ($D = 1$) has non-significant KPSS and significant PP test statistics which indicate the stationarity of the seasonally differenced series. The overall trend is then tested and both KPSS and PP test statistics are evident of presence of trend in the series (Table 1). Here seasonality along with trend is present in the differenced series and they require critical attention which can be done by means of seasonal ARIMA models.

The plot of actual series reflects that there is an increasing trend Fig.1(a), thus the first difference of the actual series is obtained and plotted. The plot of differenced (D =1 and d = 1) series Fig.1(b). shows a pattern of constant variation which indicates that this series has become stationary in mean and variance.

This stationary series is generally used for taking the decision about the possible orders of ARIMA (p, d, q) $(P, D, Q)_{[S]}$ models. From the PACF plot of the stationary series Fig. 2(a), it is observed that all of the seasonal lags i.e., lag 12, 24 and 36 have significant spikes. Hence, the order of seasonal AR component is taken as, P = 1, 2 and 3. The first non-seasonal lag of PACF plot is found to be significant indicating the possible values of non-seasonal AR component as, p = 1. Now, the seasonal order of MA components is decided by looking at the ACF plot of the stationary series Fig. 2(b). In this case, first seasonal and non-seasonal lags show a significant spike which

Table 1. Test for stationarity of the series.

Series	KPSS test			PP test		
	Statistic value	lag	p-value	Statistic value	lag	p-value
Actual	2.1894	4	0.01	-106.690	4	0.01
Differenced (D = 1)	0.0307	4	0.10	-107.16	4	0.01
Differenced (d = 1)	0.0137	4	0.10	-278.30	4	0.01

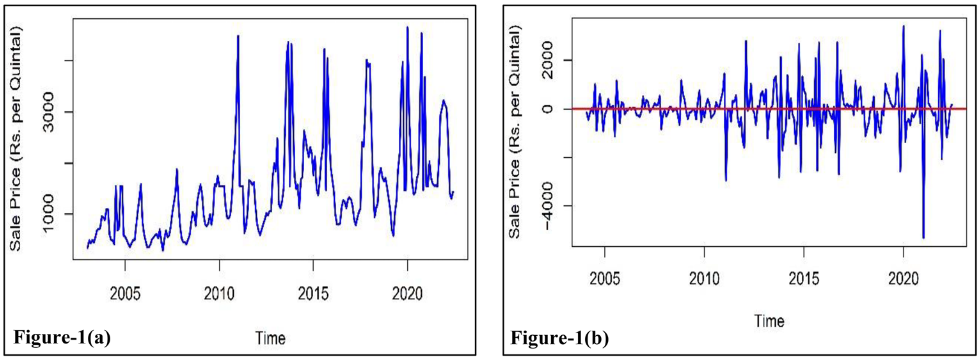

Fig. 1(a). Plot of actual values of the price of onion observed in Bolpur market. **Fig. 1(b).** Plot of lagged series of the price of onion observed in Bolpur market.

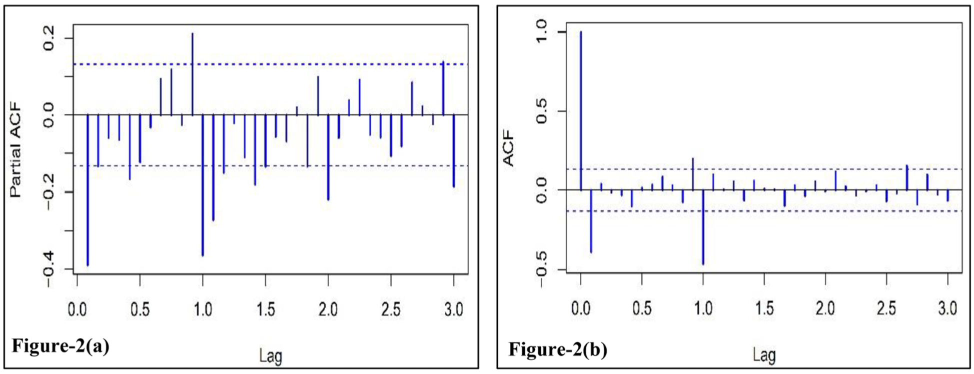

Fig. 2(a). PACF plot of stationary.

Fig. 2(b). ACF plot of stationary series.

indicate the possible values of the orders Q and q as, $Q = 1$, $q = 1$. Using these possible values of p, P, q and Q, six seasonal ARIMA models can be formed but we have considered only four models viz., ARIMA (1,1,1) $(1,1,1)_{[12]}$, ARIMA (1,1,1) $(1,1,2)_{[12]}$, ARIMA (1,1,1) $(2,1,1)_{[12]}$ and ARIMA (1,1,1) $(2,1,2)_{[12]}$.

The candidate seasonal ARIMA models are fitted to the observed data set and their respective AIC values are obtained and reported.

Table 2. Fitted seasonal ARIMA models and their AIC values.

Sl. No.	Model	Number of parameters	AIC
1	ARIMA (1,1,1) $(1,1,1)_{[12]}$	4	3524.73
2	ARIMA (1,1,1) $(1,1,2)_{[12]}$	5	3525.69
3	ARIMA (1,1,1) $(2,1,1)_{[12]}$	5	3526.45
4	ARIMA (1,1,1) $(2,1,2)_{[12]}$	6	3527.75

The lowest value of AIC with the least number of parameters is observed for ARIMA(1,1,1) $(1,1,1)_{[12]}$ model (Table 2). Thus, this model can be considered as suitable seasonal ARIMA model for forecasting the price of onion. Also, the suitability of the fitted model is in question, and it has been checked by using Box-Ljung test (Table 3). In fact, the assumption of homoscedasticity (by means of ARCH-LM test) has also been checked because the price of agricultural commodities like onion shows too much seasonal fluctuations. Here, the ARCH effect is tested by using

Table 3. Box-Ljung test for heteroscedasticity.

Model	Statistic value	*df*	p-value
ARIMA (1,1,1) $(1,1,1)_{[12]}$	41.47	1	0.0001**
ARIMA (1,1,1) $(1,1,2)_{[12]}$	44.60	1	0.0001**
ARIMA (1,1,1) $(2,1,1)_{[12]}$	43.54	1	0.0001**
ARIMA (1,1,1) $(2,1,2)_{[12]}$	41.94	1	0.0001**

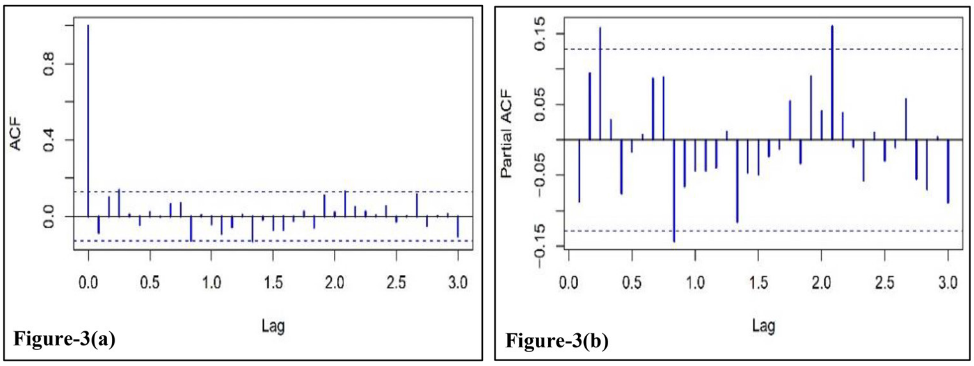

Fig. 3 (a). ACF plot of residuals obtained in fitted ARIMA model. **Fig. 3(b).** PACF plot of residuals obtained in fitted ARIMA model.

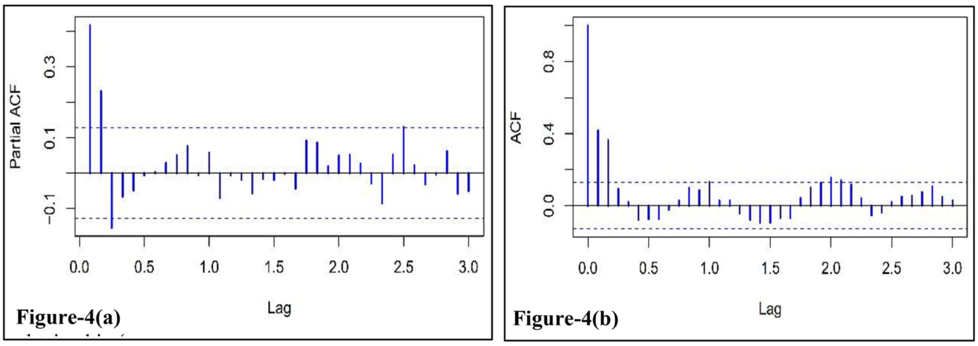

Fig. 4(a). PACF plot of squared residuals obtained in fitted ARIMA model. **Fig. 4(b).** ACF plot of squared residuals obtained in fitted ARIMA model.

observed residuals for all the fitted seasonal ARIMA models (Table 3).

For all the fitted seasonal ARIMA models, the Ljung-Box statistic is found to be significant indicating the time varying variance of the observed residuals (Table 3).

In the case of all the seasonal ARIMA models, the null hypothesis about homoscedasticity in ARCH-LM test is rejected at 1% level of significance, indicating that the residuals are heteroscedastic for all the fitted ARIMA models (Table 4). So, to fit a model which can capture this phenomenon, a model from ARCH and GARCH family has been tried and tested as below.

Table 4. ARCH-LM test for presence of ARCH effect.

Model	Statistic value	*df*	p-value
ARIMA (1,1,1) $(1,1,1)_{[12]}$	55.52	12	0.0001**
ARIMA (1,1,1) $(1,1,2)_{[12]}$	57.50	12	0.0001**
ARIMA (1,1,1) $(2,1,1)_{[12]}$	55.92	12	0.0001**
ARIMA (1,1,1) $(2,1,2)_{[12]}$	54.14	12	0.0001**

The ACF and PACF plots of the residuals obtained in ARIMA (1,1,1) $(1,1,1)_{[12]}$ model reveals that this series is white noise Figs. 3(a–b) as there is no initial lags with significant spikes in these plots. So, the ACF and PACF plots of the series of squared residuals are used for deciding the values of p and q

Table 5. Values of information criteria for the fitted GARCH models.

Model	AIC
AR(1)-GARCH(1,1)	15.494
AR(1)-GARCH(1,2)	15.482
AR(1)-GARCH(2,1)	15.502
AR(1)-GARCH(2,2)	15.492

of GARCH (p, q) model.

The PACF and ACF plots of the squared residuals suggest that the possible values of p and q as, p = 1, 2 and q = 1, 2, respectively as initial 1 and 2 Figs. 4(a–b) lags have significant spikes. Also, for the sake of simplicity, the order of the mean model specified in (1) has been taken to be, p = 1 and q = 0 i.e., AR(1) model. Using these possible values of p and q four GARCH models are formed viz., AR(1)-GARCH(1,1), AR(1)-GARCH(1,2), AR(1)-GARCH(2,1) and AR(1)-GARCH(2,2). AIC, as model selection criteria has been considered.

The lowest value of AIC is observed under AR(1)-GARCH(1,2) model but it can be noted that the difference between the AIC values of model is less than 1%, which can be neglected by considering parsimonious model with less number of parameters to be estimated. So, AR(1)-GARCH(1,1) model is considered here for forecasting the series and its conditional variance (Table 5). These models are further cross validated by using validation data set which contains the data starting from July 2020 to June 2022. APEs and MAPEs are obtained for these models.

Table 6. MAPE of different tried models (with validation data set).

Time	AR(1)-GARCH(1,1) APE	AR(1)-GARCH(1,2) APE	AR(1)-GARCH(2,1) APE	AR(1)-GARCH(2,2) APE
Jul-20	20.76	20.71	20.53	20.76
Aug-20	29.33	29.16	28.94	29.33
Sep-20	61.16	61.04	60.88	61.16
Oct-20	73.91	73.78	73.65	73.91
Nov-20	21.74	21.26	20.92	21.74
Dec-20	69.40	69.15	69.02	69.40
Jan-21	28.61	27.90	27.57	28.61
Feb-21	29.64	28.86	28.61	29.64
Mar-21	46.86	46.27	46.07	46.86
Apr-21	37.68	36.92	36.69	37.68
May-21	33.75	32.88	32.63	33.75
Jun-21	32.40	31.44	31.25	32.40
Jul-21	32.90	31.94	31.75	32.90
Aug-21	32.20	31.23	31.04	32.20
Sep-21	48.08	47.33	47.18	48.08
Oct-21	64.64	64.10	63.99	64.64
Nov-21	66.28	65.73	65.67	66.28
Dec-21	67.96	67.46	67.37	67.96
Jan-22	67.05	66.54	66.45	67.05
Feb-22	66.33	65.77	65.71	66.33
Mar-22	56.53	55.81	55.73	56.53
Apr-22	26.51	25.30	25.15	26.51
May-22	20.89	19.59	19.43	20.89
Jun-22	27.93	26.74	26.60	27.93
MAPE	**44.27**	**43.62**	**43.45**	**44.27**

It is noteworthy that AR(1)-GARCH(2,1) model has the lowest MAPE but the difference between the MAPEs of AR(1)-GARCH(2,1) and AR(1)-GARCH(1,1) models is less than 1%, which can be neglected by considering parsimonious model selection criteria. Thus, AR(1)-GARCH(1,1) model has been considered for forecasting the price in the presence of volatility (Table 6). All the estimates of the parameters are found to be significant at 1% level of significance (Table 7). Thus, this model is the suitable model for forecasting the price of onion for Bolpur market in the presence of volatility.

The best fit model i.e., AR(1)-GARCH (1,1) can mathematically be expressed as given in (5).

$$h_t = 968.51 + 0.1543\, \varepsilon^2_{t-1} + 0.8447\, h_{t-1}\,.$$

It indicates that the price of onion is too volatile. The significant positive intercept of the model reveals that if the orders of p and q terms are zero, then the volatility will be 968.51 units. Also, it is to be noted that the effect of lagged variance and error terms are positive.

The estimated mean equation of the fitted AR(1)-GARCH(1,1) model (i.e., AR(1) can mathematically be expressed as (6), $\hat{y}_t = \mu + \phi_1 y_{t-1}$, where, y_t = differenced series which is obtained as $y_t = Y_t - Y_{t-1}$, where Y_t =original value of the series at time t, $\hat{\phi}_1$ = estimate of the coefficient of the first AR component. So, the equation with estimates of the coefficients is given by

Table 7. Parameter estimates of components of AR(1)-GARCH (1,1) model.

Parameter	Estimate	Standard error	t-value	p-value
μ	1066.5393	131.1900	8.1297	0.0001**
ϕ_1	0.7900	0.0374	21.1081	0.0001**
ω	968.5100	186.5600	5.1914	0.0001**
α_1	0.1543	0.0232	6.6523	0.0001**
β_1	0.8447	0.0245	34.5223	0.0001**

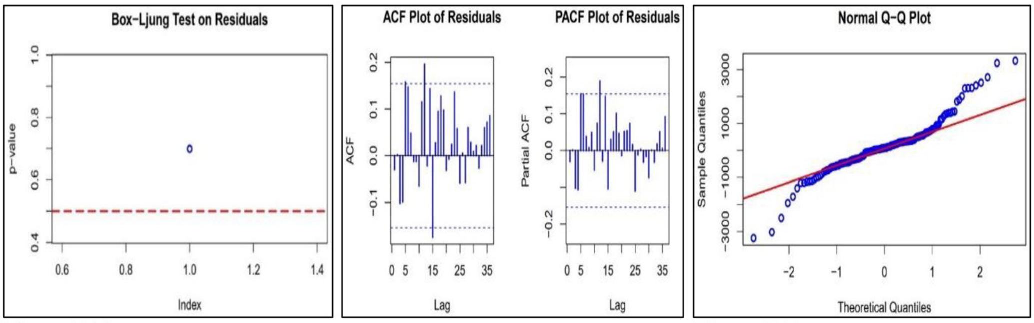

Figure-5 (a) **Figure-5 (b)** **Figure-5 (c)**

Fig. 5 (a). Probability of Box-Ljung test statistic. **Fig. 5 (b).** ACF and PACF plots. **Fig. 5 (c).** Normal Q-Q plot.

$$\hat{y}_t = \mu + \hat{\phi}_1 y_{t-1}$$
$$\hat{y}_t = 255.7854 + 0.9480\, y_{t-1}$$
$$Y_t - Y_{t-1} = 255.7854 + 0.9480\times(Y_{t-1} - Y_{t-2})$$
$$\text{(replacing } y_t \text{ with } Y_t - Y_{t-1}\text{)}$$
$$Y_t = 255.7854 + (1 + 0.9480)\, Y_{t-1} - 0.9480 Y_{t-2}$$
$$Y_t = 255.7854 + 1.9480\, Y_{t-1} - 0.9480 Y_{t-2}$$

Residual analysis

Normality and serial correlation tests on residuals of AR(1)-GARCH (1,1)

Ljung-Box test and usual ACF and PACF plots of residuals have been considered here to test the serial correlation among the residuals of AR(1)-GARCH (1,1) model. It has been found that residuals are not serially correlated because the p-value of the Ljung-Box Q statistic is more than 0.05 for which the null hypothesis about no-serial correlation cannot be rejected Fig. 5(a). None of the initial five lags in ACF and PACF plots show any significant spikes except some random spikes after 5^{th} lag in both plots indicating the absence of serial correlation Fig. 5 (b). In case of Normal Q-Q plot, most of the observations are falling on the middle line indicating a good fit of the model Fig. 5(c).

Forecast

The fitted model fulfils all the assumptions and fits the data well. So, this model has been considered for forecasting purposes.

Forecast of price and conditional variance

Considering the above situations and by using (6) and (7), the forecast of price (the mean series) along with volatility (the conditional variance) are obtained for corresponding 12-months period starting from July 2022 to June 2023 (Table 8). The forecast values of the price show a steadily decreasing trend in the price of onion started from July 2022 to June 2023.

Table 8. Final forecast values obtained by using AR (1) - GARCH (1,1) model.

Time	Price (μ_t)	Volatility (h_t)
July 2022	1356.00	576.90
August 2022	1295.00	577.50
September 2022	1247.00	578.00
October 2022	1209.00	578.60
November 2022	1179.00	579.10
December 2022	1156.00	579.70
January 2023	1137.00	580.20
February 2023	1122.00	580.70
March 2023	1111.00	581.30
April 2023	1101.00	581.80
May 2023	1094.00	582.40
June 2023	1088.00	582.90
July 2023	1084.00	583.40
August 2023	1080.00	584.00
September 2023	1077.00	584.50
October 2023	1075.00	585.00
November 2023	1073.00	585.60
December 2023	1072.00	586.10
January 2024	1071.00	586.60
February 2024	1070.00	587.20
March 2024	1069.00	587.70
April 2024	1069.00	588.20
May 2024	1068.00	588.80
June 2024	1068.00	589.30

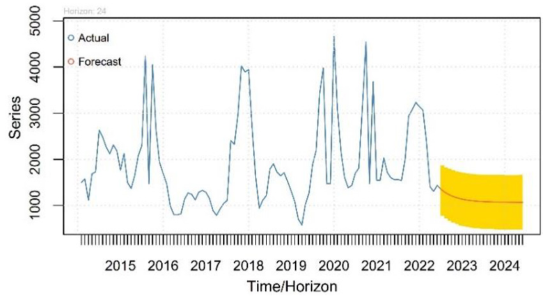

Fig. 6. Plot of forecast values obtained in fitted AR(1)-GARCH(1,1) model.

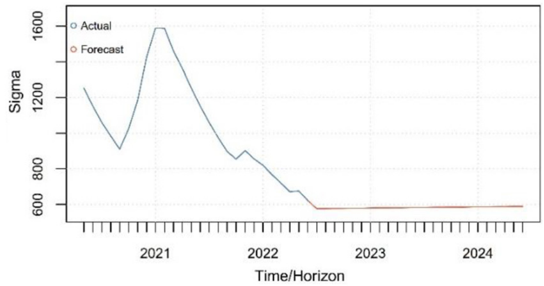

Fig. 7. Plot of forecast values of conditional standard deviation ($\sqrt{(h_t)}$) obtained by AR(1)-GARCH(1,1) model.

The plot of the forecast values of price of onion is also obtained. The forecast values show a line which is declining towards the x-axis during the period of forecast. It indicates that the price will decrease during the months of forecast i.e., July 2022 to June, 2024 (Fig. 6).

During the period of forecast the conditional variance shows a line parallel to x-axis, which indicates that the conditional variance will remain constant in that period. It can also be said that the decreasing trend in price of onion during the period of forecast will be followed by a constant conditional variance (Fig.7).

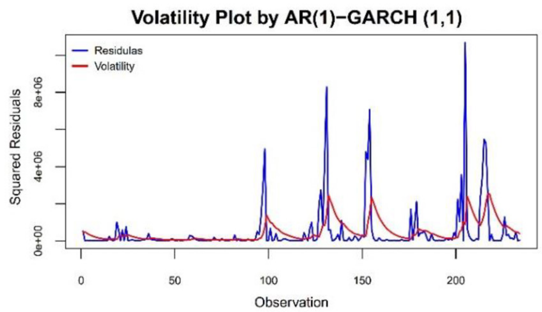

Fig. 8. Plot of volatility observed in AR(1)-GARCH (1,1) model.

Situation of volatility in the fitted model

The high values of residuals are followed by the high values of conditional variances (volatility) which indicates volatility clustering in the data (Fig. 8).

It can be noted that the price has a decreasing tendency with a constant conditional variance. In this situation, it will be profitable to sale the produce early as there is not much fluctuation in price.

CONCLUSION

After assessing the normality and testing the presence of volatility, it is found that AR(1)-GARCH(1,1) model is suitable for forecasting the volatility present in the observed data set on price of Onion at Bolpur market. The forecast of price as well as the conditional variance suggest that the volatility would be apparent and remain constant till June 2024. Forecast is also acceptable because the residuals of the fitted model are normally distributed without any serial correlation. Forecast values of the price of onion show a steadily decreasing trend which indicates that the price for a period of 24-months has some degree of stability. Considering these situations, the onion cultivators of Bolpur market should sale their produce to avoid the extra expenses in storage as price shows decreasing pattern in future.

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