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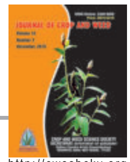

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Evaluating forecast performance of GARCH model on weekly price of onion

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ABSTRACT

The development of an effective and trust worthy forecasting method for commodities with variable price series is essential in a country like India that is heavily dependent on agriculture. Due to the simultaneous presence of non-linearity, seasonality and complexity in the data, accepting a particular model for accurately forecasting price series of commodities like onion is difficult. In this endeavour, the performance of the time series model GARCH on the volatile weekly price series of onion of Kolhapur market of Maharashtra has been evaluated. To determine whether the series is stationary, Phillips Perron (PP) and Augmented Dickey-Fuller (ADF) tests have been applied. The Lagrange multiplier test was necessary to find the presence of the autoregressive conditional heteroscedastic (ARCH) effect. Values have been predicted for the next twelve horizons after the model was tuned with the training data set and the forecasts have then been compared with the testing dataset. Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) values have been used to determine accuracy. As seen, GARCH model has outperformed ARIMA model in dealing with the price dataset used in our study.

***Keywords*:** Heteroscedasticity, MAPE, non-linearity, stationarity, volatility

In recent decades, the scientific community has become interested in the dynamic research area of time series modelling and forecasting. Both the government and farmers utilise forecasts of agricultural output and prices to make judgements regarding their future plans and activities. While making decisions about production and marketing that have potentially a financial impact, farmers rely on price projections. The projection of future values using historical records/ data and various models is known as time series forecasting. In the literature, there are two basic categories for time series analysis: linear models and non-linear models. In contrast to non-linear models, which can handle data with non-linear patterns, linear models are favoured for time series with linear patterns. Nonlinear time series have traits that are impossible for linear processes to explain, such as asymmetric cycles, time-varying variance, thresholds, breaks, and higher-moment structures.

Agriculture is a risky affair with respect to production and marketing as it is governed by numerous factors like quality and quantity of inputs, standardised cultivation practices and also the demand of that commodity after harvesting period. Natural calamities and weather-related fluctuations in farm productivity worsen this problem of risk and lead the prices of agricultural commodities to react quickly to both real and assumed changes in supply and demand situations. This is the reason price data for agricultural commodities are inherently noisy and unstable. Onion has been that commodity in the recent years which has shown surprising changes in its price at various time of the year due to the gap between demand and supply and therefore its price series in any market of India is highly volatile. Hence, this study tries to delve into the price forecasting of onion from one of the markets in India.

Stationarity is a key factor in dealing with time series data because it has a big impact on how our dataset is being perceived and predicted by the model in use. The majority of time series models make the assumption that each point is independent of the others for forecasting or making predictions about the future. When the dataset is stationary, this is the best indication of such independence of data points. To be termed stationary, data must have constant mean and variance throughout time, among other statistical properties of the system. The basic pattern of the data should not change, but this does not indicate that the values for each data point must be the same. The stationarity behaviour can be evaluated using a time plot or a test method like the Phillips-Perron (PP) test or the Augmented Dickey Fuller (ADF) test. The time series is referred to as nonstationary in nature if both the mean and variance change over time. Differentiating can be employed to attain stationarity if the time series' mean is nonstationary. If the variance of the time series is nonstationary, a number of

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transformation approaches, such as taking the logarithm and the Box-Cox transformation, can be applied.

The series is volatile when a few error terms are larger than the others and gives rise to unique behaviour of the series known as heteroscedasticity. Volatility, to put it simply, is a series' abrupt, unexpected rise or decrease that could annoy stakeholders.

In literature, price forecasting of agricultural crops by ARIMA model is easily available because it is the most widely used model. It was used to forecast wholesale paddy prices for five major rice producing states of India (Kathayat *et al*., 2020) and also to predict cultivated area, production and productivity of onion in India (Mishra *et al*., 2013). It has been applied to predict the increase in price and demand of onion in the near future (Darekar *et al.,* 2016). For the modelling and forecasting of financial and economic phenomena, the GARCH(Generalised Autoregressive Conditional Heteroscedasticity) models are extensively employed. For an instance, it has been used to forecast stock market volatility of SSE Composite Index (Lin, 2018). ARCH (Autoregressive Conditional Heteroscedasticity) and GARCH models along with AR (Autoregressive) specification were combined to make further advancements in volatility forecasting accuracy. Researchers have employed non-linear models extensively over the past two decades and discovered several AR-GARCH model combinations that work best in diverse contexts as reported by previous workers (Jordaan *et al.*, 2007; Paul *et al*., 2009; Sundaramoorthy *et al.*, 2014). However, in time-series forecasting, the GARCH (1, 1) model is the mostly preferred GARCH formulation because of being very simple yet delivering good fit to volatile data series and performing accurate predictions.

MATERIALS AND METHODS

As previously mentioned, heteroscedasticity is the term for when a few error terms dominate the rest and dictate a series' particular behaviour. This is why a series is deemed volatile when this occurs. The popular and non-linear autoregressive conditional heteroscedastic (ARCH) model was developed by Engle (1982) to cope with heteroscedasticity. Bollerslev (1986) expanded the model and proposed the Generalized ARCH (GARCH) model for a sparse representation of ARCH. The conditional variance in the GARCH model is also a linear function of its own lags. This model, like ARCH, is a weighted average of previously squared residuals, but unlike ARCH, it contains decreasing weights that never reach zero.

In our study, Lagrange multiplier test has been applied to detect the presence of autoregressive conditional heteroscedastic (ARCH) effect before going to fit the GARCH model.

GARCH model

The Autoregressive Conditional Heteroscedastic ARCH (q) model formula for the series ϕ_t is given as below :

$$\phi_t \mid \beta_{t-1} \sim \mathrm{N}\,(0, l_t) \qquad (1)$$

Here β_{t-1} signifies information available up to time t-1 and $l_t = k_0 + + \sum_{i=1}^{q} k_i \phi_{t-i}^2$ (2)

Where $k_0 > 0$, $k_i \geq 0$ for all i and $\sum_{i=1}^{q} k_i < 1$ are the conditions necessary to be satisfied to ensure finite unconditional variance non-negativity and of the stationary $\{\phi_t\}$ series.

In the Generalized ARCH (GARCH) model introduced by Bollerslev in 1986, conditional variance is likewise a linear function of own lags and takes the following structure:

$$l_t = k_0 + \sum_{i=1}^{q} k_i \phi_{t-i}^2 + \sum_{j=1}^{p} m_j l_{t-j} \qquad (3)$$

For the conditional variance to be positive, we need to take care of the following need:

$$k_0 > 0,\ k_i \geq 0\ i = 1,2,\ldots,q\,;\ m_j \geq 0\,, j = 1,2,\ldots,p$$

The GARCH (p,q) phenomenon will be weakly stationary under the only condition that $\sum_{i=1}^{q} k_i + \sum_{j=1}^{p} m_j < 1$

We can also express GARCH model in form of ARMA model as $\theta_t = \phi_t^2 - l_t$.

Then from eq. (3), we get

$$\phi_t^2 - k_0 + \sum_{i=1}^{Max\,(p,q)} (k_i + m_i)\, \phi_{t-i}^2 + \theta_t + \sum_{j=1}^{p} m_j \theta_{t-j} \qquad (4)$$

Thus a GARCH model can be considered as an extended form of ARMA approach to the squared series $\{ \phi_t^2 \}$.

Accuracy Measures:

Mean Absolute Percentage Error :

$$MAPE = \frac{1}{h} \sum_{s=1}^{h} |z_s| / f_s \times 100$$

Where f_s is the time series, h is the forecast horizon, z_s is the residual of the time series and $z_s = f_s - \hat{f}_s$ where $\hat{f}_s$ is the predicted value for time s.

Root Mean Squared Error :

$$RMSE = \sqrt{\frac{1}{h} \sum_{s=1}^{h} (z_s)^2}$$

Where z_s denotes the residual and h is the forecast horizon.

Data :

In this study, weekly price series of Onion has been collected from the website of Agmark for the period of January, 2015 to October, 2022. The data on price refers to modal price in a week and pertains to Kolhapur market which is one of the biggest markets of Maharashtra for arrival of onion. First 385 data points have been used for model tuning and the remaining 12 for validation purpose.

RESULTS AND DISCUSSION

Table 1 shows the descriptive statistics of the weekly price series of onion. The skewness value indicates asymmetry of the price series alongside kurtosis suggesting the data to be little platykurtic in nature. The time series plot in Fig. 1 illustrates clearly how volatility is evident over a wide time span. The results of Phillips-Perron (PP) and Augmented Dickey Fuller (ADF) test statistic at 1% level of significance as seen (Table 2) indicates non-stationary of data and hence we go for first differencing as a measure to overcome non-stationarity of data. The differenced series is stationary as indicated by the test values in the Table 2. The null hypothesis of both the tests is that the data series is non-stationary. According to the literature, ARCH/GARCH models have advantages over ARIMA and different linear models, making them suitable for assessing price volatility (Jordaan *et al*., 2007). First, it is simple to differentiate between unpredictable and predictable parts of the price process and secondly, heteroscedasticity is taken into account and modelling the variance presents no issues (Lama *et al*., 2015). Thus, in our analysis, the GARCH model was chosen above the ARIMA model.

ARIMA model

R software has been used for all the modelling and forecasting applications in this study. Various combinations of the ARIMA models have been put under trial after first differencing of the series. Among all, the ARIMA(2,1,3) model was found superior as it presented lowest AIC and BIC values for the data set. Table 3 provides the parameter estimates of the ARIMA model in addition to the standard errors in brackets. High RMSE and MAPE values were obtained for the training and testing datasets when this model was fitted to our data set and forecasted, demonstrating that the ARIMA is ineffective for modelling and forecasting volatile data (Table 4). Thus, it was felt that these series should be modelled using a nonlinear model like GARCH.

Testing of ARCH effect

The fundamental concept of the Box-Jenkins method is that the residuals don't change over time. In order to determine whether residuals actually remain constant, the ARCH-LM test was applied to the square of the residuals that were produced on fitting the ARIMA model. The null hypothesis of this test is absence of ARCH effect but presence of it is indispensable for applying GARCH. Unsurprisingly, the results of the test brought out the ARCH effect in our series (Table 5).

Fitting of GARCH model

Following the ARCH-LM test, the GARCH framework was applied to the price series followed by forecasting. Based on in-sample performance, the AR(2)-GARCH(1,1) model was determined to be the most effective model. Table 6 provides estimates of the GARCH model's parameters for both series, along with the standard errors of those estimates in brackets. The findings showed that onion price series have persistent volatility, with alpha and beta being somewhat near to one.

Forecast

Prices for twelve weeks have been forecasted with the AR(2)-GARCH(1,1) model and the accuracy of the model has been calculated further as depicted in the table 7 and 8 respectively. Fig. 2 demonstrates the performance of GARCH in the form of graphical representation. Considering that the weekly price predicted are the prices per quintal of onion, we see that even RMSE value above two hundred is a significantly good result. These predictions for the future price of onion can help farmers to decide the area for onion crop and marketing. In addition, growers can decide whether to sell stored onions right away or wait a few months.

CONCLUSION

The performance of GARCH model has been studied using weekly onion price series of Kolhapur market. The prices for twelve weeks were forecasted using the same. For the series, the AR(2)-GARCH (1,1) has outclassed the ARIMA(2,1,3) model as evident in forecast accuracy values. Low RMSE and MAPE values compared to ARIMA model serve to demonstrate the effectiveness of the GARCH model for time series modelling. Other agricultural price series with volatility such as for crops like potato, maize and sugarcane can be forecasted using the methodology utilised in this study. The Indian farming community can benefit greatly from this type of application of non-linear time series models.

Table 1 : Summary statistics of price series

Statistics	Weekly data
Observations	397
Mean (Rs.)	1474.59
Median (Rs.)	1200.00
Maximum (Rs.)	6333.33
Minimum (Rs.)	400.00
Standard Deviation (Rs.)	947.59
Skewness Not discussed done	1.64
Kurtosis Not discussed done	2.95

Table 2 : Stationarity test for the data

Series		ADF test	P value	PP test	P value
Kolhapur onion weekly price data	Level	3.88	0.02	24.78	0.02
	Differenced	7.93	<0.01	45.70	<0.01

Table 3 : Parameter estimates of ARIMA(2,1,3) Model

Series	Parameter	Estimate
Kolhapur onion weekly price data	AR(1)	1.53 (0.08)
	AR(2)	0.84 (0.08)
	MA(1)	1.59 (0.01)
	MA(2)	1.02 (0.11)
	MA(3)	0.09 (0.06)

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

Table 4 : ARIMA model RMSE and MAPE values

Series	RMSE	MAPE
Training set	**289.91**	**9.92**
Testing set	**108.78**	**7.75**

Note: RMSE: Root Mean Square Error, MAPE: Mean Absolute Percentage Error

Table 5 : ARCH LM Test

Kolhapur onion weekly price series	Chi-square	P value
	172.21	**<0.01**

Table 6: Estimates of the parameters of the AR(2)-GARCH(1,1) model

Kolhapur onion weekly price series	alpha	beta	AIC
	0.53 (0.08)	0.46 (0.05)	13.30

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

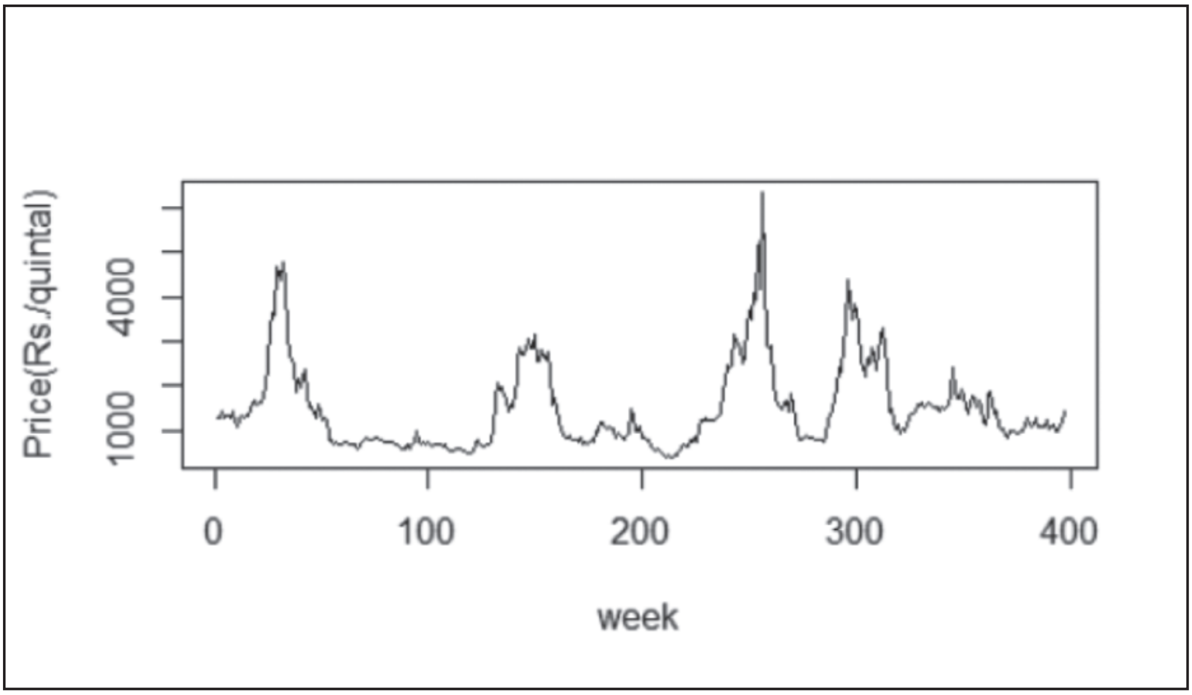

Fig. 1: Time series plot of weekly price series of onion

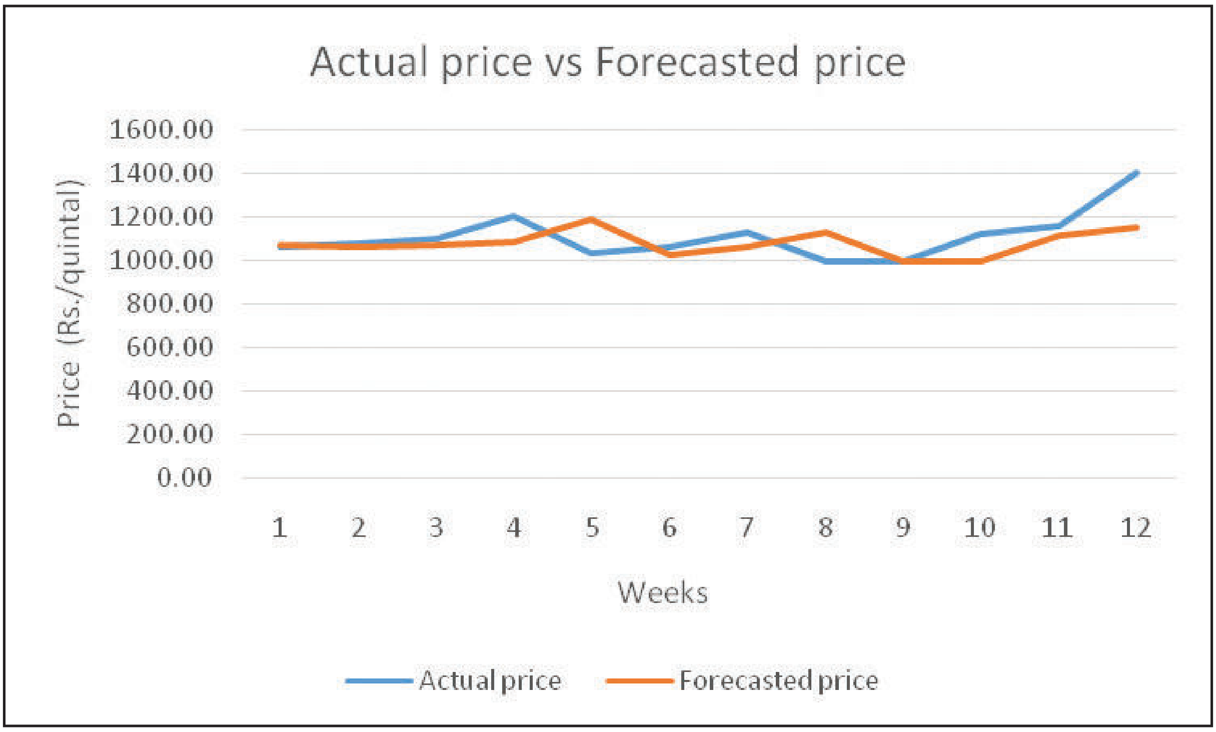

Fig. 2: Comparison of actual and forecasted price by GARCH model

Table 7: Forecasts of the weekly onion price by GARCH

Weeks	Actual price	Forecasted price
1	1066.67	1070.41
2	1080.00	1062.05
3	1100.00	1065.79
4	1200.00	1085.28
5	1033.33	1188.53
6	1066.67	1025.18
7	1133.33	1060.46
8	1000.00	1127.69
9	1000.00	994.15
10	1120.00	993.73
11	1160.00	1113.40
12	1400.00	1153.26

Table 8: GARCH model RMSE and MAPE values

Series	RMSE	MAPE
Training set	256.91	7.92
Testing set	100.25	6.05

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