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Modeling and Forecasting of All India Monthly Average Wholesale Price Volatility of Onion: An Application of GARCH and EGARCH Techniques

Pushpa [a], Sanjeev [a*], Preeti [a] and Pankaj Dahiya [b]

[a] *Department of Mathematics and Statistics, CCSHAU, Hisar (Haryana), India.*
[b] *Department of Agricultural Meteorology, CCSHAU, Hisar (Haryana), India.*

Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

The study utilized log returns of all India monthly average wholesale prices(Rs/Q) of onion over period Jan-2010 to Dec-2021 and employed the autoregressive integrated moving-average (ARIMA), generalized autoregressive conditional heteroscedastic (GARCH), exponential GARCH (EGARCH) and threshold GARCH (TGARCH) modeling techniques with different error distribution such as normal and student-t. Lagrange multiplier test has been applied to detect the presence of autoregressive conditional heteroscedastic (ARCH) effect. The Ljung-Box test has been used for testing the autocorrelation exists in a time series. A comparative study of the above models has been done in terms of root mean square error (RMSE), mean absolute percentage error (MAPE) and R-square. The residuals of the fitted models have been used for diagnostic checking. The study has revealed that the ARMA (2,1) model is the best fitted modeling the mean equation for the

**Corresponding author: E-mail: sirohisanju20@gmail.com;*

log returns whereas in the variance equation, basic GARCH (1,1) and EGARCH (1,1) models with student-t innovations are appropriate in describing the symmetric and asymmetric behaviors of the log returns on the basis of smaller value of AIC (Akaike information criterion) and BIC (Bayesian information criterion).

Keywords: Price volatility; ARIMA; GARCH; EGARCH; TGARCH.

1. INTRODUCTION

“Volatility forecasting is an important tool in financial economics such as risk management and asset allocation since an understanding of future volatility can help minimize their losses. Volatility is not directly observable in practice and thus needs to be estimated from the underlying price of an asset. The estimating the volatility with log return as underlying series is that the volatility has four commonly seen characteristics” [1]. Volatility clusters means that the variance of the series changes over different periods [2]. “Volatility jumps are infrequent since volatility changes in a continuous matter” [3]. “Volatility varies within some fixed range and does not diverge to infinity” [4]. “Big price drops seem the have a larger effect on the volatility than an equally large price increase, i.e., asymmetric effects. The fourth characteristic is known as the “leverage effect” and is frequently encountered in financial time series. Since these four phenomena have been found to characterize the movement of volatility in financial time series, they have played a significant role in the development of volatility forecasting models. The earlier theoretical models on volatility assumed constant variance, i.e., homoscedastic regression models, which do not reflect the properties of volatility. To better reflect the characteristics of volatility in the models” [3]. Engle [5] proposed “the Autoregressive Conditional Heteroscedasticity (ARCH) model. Unlike the traditional models of constant variance, the ARCH process accounts for the time-varying conditional variance of financial time-series using lagged disturbances. The disadvantage of the ARCH was that it had to use many parameters to capture the dynamics of conditional variance”. Due to this, Bollerslev [2] proposed a “generalized extension to the ARCH, the Generalized ARCH (GARCH), which allowed for a more flexible lag structure that could reduce the number of parameters in the model. Both the ARCH and GARCH can capture the commonly seen characteristics of volatility clustering and leptokurtosis”. “The disadvantage of these models is that they fail to capture the leverage effect due to being symmetric models” [6,7]. “Many asymmetric extensions to GARCH have thereafter been proposed to address the leverage effect *i.e.* negative shock in asset return will have a larger effect on the volatility of the series than an equally large positive shock” [8]. Examples of asymmetric extensions are the Exponential GARCH (EGARCH) by Nelson [9], and Glosten-Jaganathan-Runkle (GJR) by Glosten, Jaganathan and Runkle [10]. The purpose of this paper is to investigate the volatility forecasting performance of symmetric and asymmetric GARCH models for all India monthly average wholesale prices of onion. Burark et al. [4] examined “the performance of the exponential smoothing model, ARIMA, using monthly wholesale pricing data of coriander in the Kota market of Rajasthan over the period of April 2000 to May 2011”. Ali (2013) investigated “the effectiveness of various asymmetric models such as EGARCH model, IGARCH model, TGARCH model, GJR-GARCH model, NGARCH model, AVGARCH model and APARCH model to analyze daily data of fecal indicator bacteria densities near Huntington Beach in Ohio, United States for the period of 2006 to 2008”.

The restrictions of this paper are the use of GARCH, EGARCH and TGARCH as forecasting models. The evaluation of the volatility forecasting performance of the models is on all India monthly average wholesale prices of onion and not on a series during “normal” circumstances. This is interesting the variance of a financial series on average increase and there are big downturns in price which should make the leverage effect more central. The performance measures such as Relative deviation percentage (RD%), Mean Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE) and R-square are used to compare and evaluate the forecasting performance of the models, i.e., which of the models achieves a predicted volatility closest to the realized volatility.

2. METHODOLOGY

2.1 ARCH Model

ARCH models are based on the variance of the error term at time t depends on the realized values of the squared error terms in previous time periods. The model is specified as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \cdots + \alpha_q u_{t-q}^2$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} u_{t-q}^2$$

Since σ_t^2 is a conditional variance, its value must always be strictly positive; a negative variance at any point in time would be meaningless. To ensure that the conditional variance is strictly positive coefficient in the equation must be $\alpha_0 > 0$, and $\alpha_i \geq 0$, $i = 1, \ldots, q$, $\alpha_1 + \ldots + \alpha_q < 1$ for ensuring $\{\sigma_t^2\}$ as weak stationary.

2.2 Generalized-ARCH Model (GARCH)

The process allows the conditional variance of variable to be dependent upon previous lags; first lag of the squared residual from the mean equation and present news about the volatility from the previous period which is as follows:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2$$

$\alpha_0 > 0$, $\alpha_i \geq 0$, $i = 1, \ldots, q$; $\beta_j \geq 0$, $j = 1, \ldots, p$; $\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j < 1$ for ensuring $\{\sigma_t^2\}$ as weak stationary. Enocksson and Skoog (2012) pointed out some limitations on GARCH model. The most important one is GARCH model cannot capture the asymmetric performance.

2.3 Exponential GARCH (EGARCH) Model

Nelson [9] proposed the exponential GARCH (EGARCH) model includes a form of leverage effects in its equation.

$$\log\sigma_t^2 = c + \sum_{i=1}^{p} g(Z_{t-1}) + \sum_{j=1}^{q} \beta_j \log\sigma_{t-j}^2$$

$$g(Z_{t-1}) = \gamma_1 Z_{t-1} + \alpha_1(|Z_{t-1}| - E(|Z_{t-1}|))$$

Define $Z_{t-1} = \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ and the logarithm of the conditional variance equals to:

$$\log(\sigma_t^2) = c + \sum_{j=1}^{q} \beta_j \log \sigma_{t-1}^2 + \sum_{i=1}^{p} \alpha_i \left(\left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| - E\left(\left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| \right) \right) + \sum_{i=1}^{p} \gamma_1 \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$$

α_i represents the symmetric effect, β_j measures the persistence in conditional volatility shock and reflects the asymmetric performance. EGARCH (1,1) can be expressed as:

$$\log \sigma_t^2 = \omega + \beta_1 \log \sigma_{t-1}^2 + \alpha_1 \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$$

Where α_1 represents the symmetric effect of the model, β_1 measures the persistence in conditional volatility shock. Large value of this implies that volatility will take a long time to die out following a crisis in the market.

If $\gamma < 0$, then leverage effect exists and negative shocks (bad news) generate more volatility than positive shocks (good news) of the same magnitude and $\gamma > 0$, it implies that positive shocks generate more volatility than negative shocks of the same modulus. The volatility shock is asymmetric when $\gamma \neq 0$. If on the other hand $\gamma = 0$, then the model is symmetric

2.4 GJR-GARCH Model

Glosten, Jagannathan and Runkle [10] proposed GJR-GARCH model, another asymmetric model, is also known as threshold GARCH (TGARCH) model. GJR-GARCH model is written by

$$\sigma_t^2 = c + \sum_{j=1}^{p} \beta_j \sigma_{t-1}^2 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{k=1}^{r} \gamma_k \varepsilon_{t-k}^2 I_{t-k}(\varepsilon_{t-k} < 0)$$

In GJR-GARCH model, the sign of the indicator term captures the asymmetry and Patrick, Stewart and Chris (2006) describe it in details in their article.

$$I_t = \begin{cases} 1, \text{if } \varepsilon_t < 0, \text{badnews} \\ 0, \text{if } \varepsilon_t \geq 0, \text{goodnews} \end{cases}$$

Where I_t is an indicator function, when the residual (ε_t) is smaller than zero, the indicator term (I_t) equals to one or equals to zero when the residual is not smaller than zero.

The conditional variance for the simple GJR-GARCH (1,1) model is defined by:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1}$$

Where I_t=1 if ε_t is negative and 0 otherwise. In the TGARCH (1,1) model, volatility tends to increase with bad news ($\varepsilon_{t-1} < 0$) and decreases with good news ($\varepsilon_{t-1} \geq 0$). Good news has an impact of α_1 whereas bad news has an impact of $\alpha_1 + \gamma$. If leverage effect parameter $\gamma > 0$ and statistically significant then the leverage effect exists. If $\gamma \neq 0$, the shock is asymmetric, and if $\gamma = 0$, the shock is symmetric. The persistence of shocks to volatility is measured by $\alpha_1+\beta_1+\gamma/2$.

2.5 Distribution of the Error Term

This paper mainly introduces two distributions. One is normal distribution and other one is student-t distribution.

2.5.1 Normal distribution

The probability density function of Z_t is given as follows,

$$f(Z_t) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{1}{2}\left(\frac{Z_t - \mu}{\sigma}\right)^2\right\}$$

where μ is mean and σ is standard deviation.

2.5.2 Student t-distribution

The probability density function of Z_t is given as follows,

$$f(Z_t) = \frac{\Gamma\left(\frac{v+1}{2}\right)}{\Gamma\left(\frac{v}{2}\right)\sqrt{(v-2)\pi}}\left(1 + \frac{z_t^2}{v-2}\right)^{-\frac{1}{2}(v+1)}$$

Where v is the number of degrees of freedom, $2 < v \leq \infty$, and is Γ gamma function. When $v \to \infty$, the student-t distribution nearly equals to the normal distribution. The lower the v, the fatter the tails.

2.6 Model Selection

Model Selection When comparing among different specification of ARMA-GARCH models, then we select an appropriate model based on Akaike Information Criteria (AIC) and Bayesian Information Criterion (BIC). The AIC and BIC can be computed as

AIC = −2ln(residual sum of squares) + 2k
BIC = −2ln(residual sum of squares) + ln(N)k

Where N is the number of observations, and k is the number of estimated parameters. The minimum value of AIC and BIC is selected as the better model when comparing among models.

2.7 Model Evaluations

The volatility forecasting performance of models is evaluated using four statistical measures: Relative deviation percentage (RD%), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and R-square, are defined by the formula:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{t=T_1}^{T}(O_i - E_i)^2}$$

$$\mathrm{MAPE} = \frac{100}{N}\sum_{i=1}^{n}\frac{O_i - E_i}{O_i}$$

$$\mathrm{RD\%} = \frac{O_i - E_i}{O_i} \times 100$$

$$R^2 = 1 - \frac{\sum(O_i - E_i)^2}{\sum(O_i - \bar{O})^2}$$

Where, O_i, $\bar{O}$ and E_i are the observed, mean and predicted values and N is the number of observations for which estimation has been done. When comparing among ARMA-GARCH models, the smallest value of RD, RMSE and MAPE and Highest value of R-square are chosen as the best appropriate forecast volatility model.

3. DATA

Time series data on all India monthly average wholesale prices of onion (prices in rs/quintal) over period Jan-2010 to Dec-2021 (total number of observations 144), collected from agriculture market (Source: https://agmarknet.gov.in/*)*. The first 132 observations (Jan-2010 to Dec-2020) are used for model building and parameter estimation, while the next 12 observations (Jan-2021 to Dec-2021) are used for post-validity checking.

The monthly log returns (r_t) are calculated as the continuously compounded returns which are the first differences of log prices of consider time series.

$$r_t = \log\left(\frac{P_t}{P_{t-1}}\right)$$

where P_t and P_{t-1} are all India monthly average wholesale prices of onion at the current month and previous month respectively.

Table 1. Log returns descriptive statistics for all India monthly average wholesale prices of onion

N	Mean	Median	Max.	Min.	SD	Skew.	Kurt.
144	0.61	0.37	62.85	-74.22	21.95	-0.17	1.09

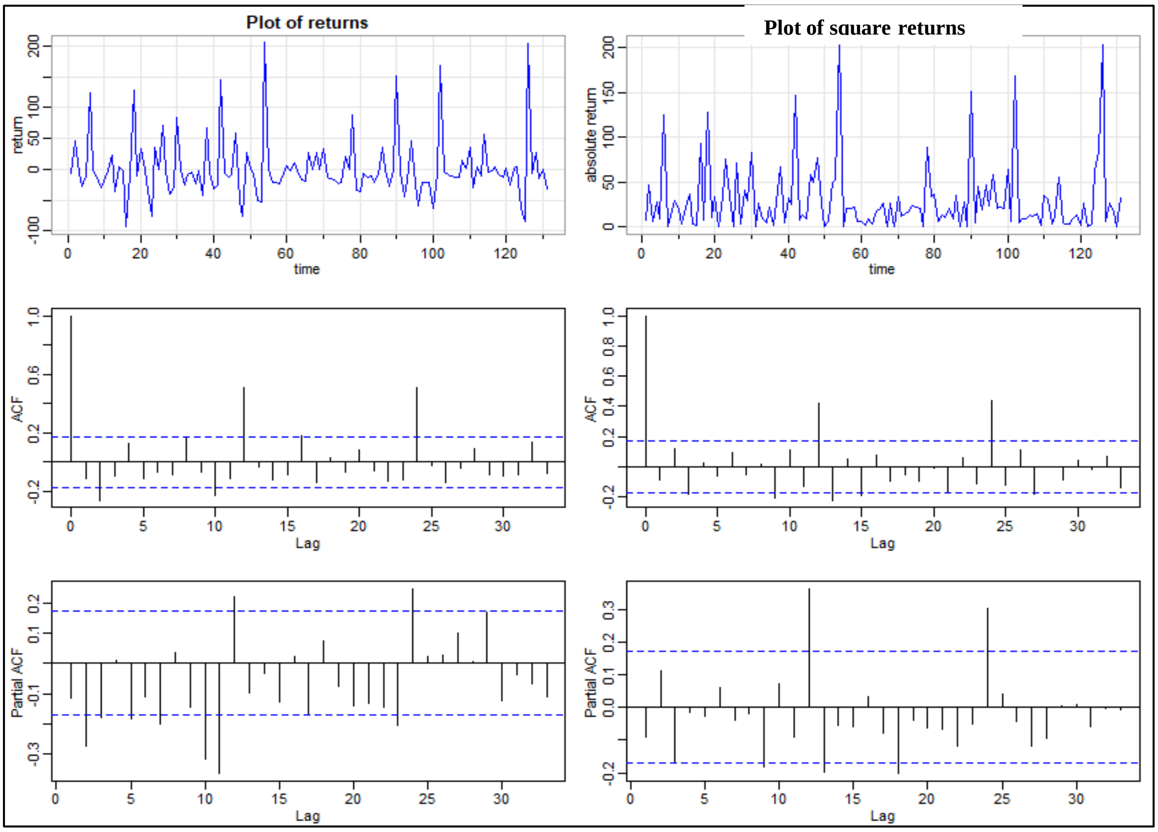

Fig. 1. Plots of log returns and absolute returns for all India monthly average wholesale price of onion

Table 2. Lagrange multiplier test for log returns of all India monthly average wholesale prices of onion

	Null Hypothesis	Test Statistics	P-value
LM	Presence ARCH effect	1.75	0.002
KPSS	Time series is stationary	0.03	0.1

From this table, the skewness is -0.17 (negative skewed), is not zero which means that the rate of log returns is not symmetric, and kurtosis is 1.09, is smaller than three which means that the distribution of log returns is flat (platykurtic) relative to the normal. Plots of log returns and square returns shown in Fig. 1, indicate that presence of autocorrelation in log returns and square return.

Lagrange multiplier and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests are applied to detect the presence of autoregressive conditional heteroscedastic (ARCH) effect and stationarity around a deterministic trend in log returns time series [11,12]. Log returns time series has stationary and presence of ARCH effect are shown in above Table 2. Based on the assumption of 5% significance level, all of the p-values are smaller than 0.05, which means that not reject the null hypothesis otherwise rejected.

4. RESULTS

In this part, ARMA-GARCH, ARMA-EGARCH and ARMA-TGARCH models are used to estimate and forecast the log returns of all India monthly average wholesale prices of onion under the different error distributions i.e. normal and student-t distributions and then compare the forecasting performance measures such as RD (%), RMSE, MAPE and R-square and choose the appropriate volatility forecast model.

4.1 Selection of Models for Mean Equation and Variance Equation

Selection of suitable mean equation ARMA (p, q) and variance equation GARCH (p, q), EGARCH (p, q) and TGARCH (p,q) model for log returns of all India monthly average wholesale prices of onion. By observing the autocorrelation and partial autocorrelation of log returns, the tentative order of p and q can be acquired.

Compare ARMA (2,1)-GARCH (1, 1), ARMA (2,1)-EGARCH (1, 1) and ARMA (2,1)-TGARCH (1, 1) models under different error term's distributions. After comparing the AIC and BIC values for different models, the more suitable ARMA (2,1)-GARCH (1,1) and ARMA (2,1)-EGARCH (1,1) models with Student-t distribution will be picked up with the smallest value of AIC and BIC shown in Table 3. The estimated parameters of ARMA (2,1)-GARCH (1,1) Model and ARMA (2,1)-EGARCH (1,1) with Student-t shown in the Table 4 and Table 5 respectively.

$$Y_t = 0.169 + 1.144Y_{t-1} - 0.347Y_{t-2} + \varepsilon_t + 0.751\varepsilon_{t-1}$$

The conditional variance equation of the basic GARCH (1,1) model is presented as:

$$\sigma_t^2 = 0.435 + 0.027\varepsilon_{t-1}^2 + 0.9078\sigma_{t-1}^2$$

We observe that all parameters of the ARMA (2,1)-GARCH (1,1) model are significant. ARCH term α_1 = 0.027 and GARCH term β_1 = 0.907. Large value of the GARCH term shows that the effect of volatility shocks to the conditional variance takes a very long time (long memory process), and the volatility is quite persistent. The sum of the ARCH and GARCH parameters α_1 + β_1= 0.9348 shows that the stationarity condition of α_1 + β_1 <1 is satisfied. This also shows that the conditional variance process of the log returns series is stable and predictable.

In the variance equation, the estimated EGARCH (1,1) model is presented in equation below

$$\log\sigma_t^2 = 0.155 + 0.922\log\sigma_{t-1}^2 + 0.031\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| - 0.110\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$$

Table 3. Model Selection Criteria

Model	Distribution	AIC	SIC
ARMA (2,1)-GARCH (1,1)	ND	4.74	4.82
ARMA (2,1)-GARCH (1,1)	STD	4.69	4.78
ARMA (2,1)-EGARCH (1,1)	ND	4.70	4.79
ARMA (2,1)-EGARCH (1,1)	STD	4.68	4.75
ARMA (2,1)- TGARCH (1,1)	ND	4.73	4.83
ARMA (2,1)-TGARCH (1,1)	STD	4.72	4.83

Table 4. Parameter Estimates of ARMA (2,1) - GARCH (1,1) Model with Student-t

Mean Equation	Coefficient	Std. Error	t-statistics	P-value
Φ_0	0.16	0.17	0.97	0.03
AR (1) Φ_1	1.14	0.14	7.85	0.00
AR (2)Φ_2	-0.34	0.06	-5.47	0.00
MA (1)θ_1	-0.75	0.14	-5.15	0.00
Variance Equation				
Ω	0.0435	0.358	1.215	0.02
α_1	0.027	0.024	1.091	0.002
β_1	0.9078	0.066	13.63	0.000
V	8.919	3.520	2.533	0.011
α_1 + β_1	0.934			

Table 5. Parameter Estimates of ARMA (2,1) - EGARCH (1,1) Model with Student-t

	Coefficient	Std. Error	t- statistics	P-value
Mean Equation				
Φ_0	06.218	0.111	1.956	0.05
AR (1) Φ_1	1.214	0.094	12.820	0.00
AR (2)Φ_2	-0.338	0.054	-6.176	0.00
MA (1)θ_1	-0.852	0.073	-11.529	0.00
Variance Equation				
Ω	0.155	0.041	3.739	0.001
α_1	0.031	0.024	2.752	0.005
β_1	0.922	0.007	133.95	0.000
γ	-0.111	0.040	-2.727	0.001
V	16.525	13.854	1.192	0.000
$\alpha_1 + \beta_1$	0.953			

We observe that all parameters of the ARMA (2,1)-EGARCH (1,1) model are significant and the shock persistence parameter (β_1=0.9223) is very close to unity implying that the conditional variance has long memory and volatility shock is quite persistence. The EGARCH (1,1) model also shows that the leverage effect parameter (γ= -0.110) is negative and statistically significant suggesting that past negative shocks have greater impact on subsequent volatility than positive shocks of similar magnitudes.

4.2 Diagnostic Checking for Selected Models

Diagnostic checking for selected suitable ARMA (2,1)-GARCH (1,1) and ARMA (2,1)-EGARCH (1,1) models for log returns of all India monthly average wholesale prices of onion.

The standardised residuals are used to determine whether the model is appropriately specified. The ACF and PACF plots (Figs. 3 and 4) of the standardised residuals derived using ARMA (1,2)-GARCH (1,1) and ARMA (1,2)-EGARCH (1,1) revealed that autocorrelations are not substantially different from zero.

To confirm the appropriateness of the model, the statistical tests, Ljung-Box test and ARCH-LM test are used for checking the autocorrelation and ARCH effect exists in standardised residuals of selected suitable models. The p-value of both the tests are found to be greater than 0.05 (at 5% level of significance) for all the lags as shown in Table 6, accepting the null hypothesis of no autocorrelation and no ARCH effect in ARMA (2,1)-GARCH (1,1) and ARMA (2,1)-EGARCH (1,1) models residuals.

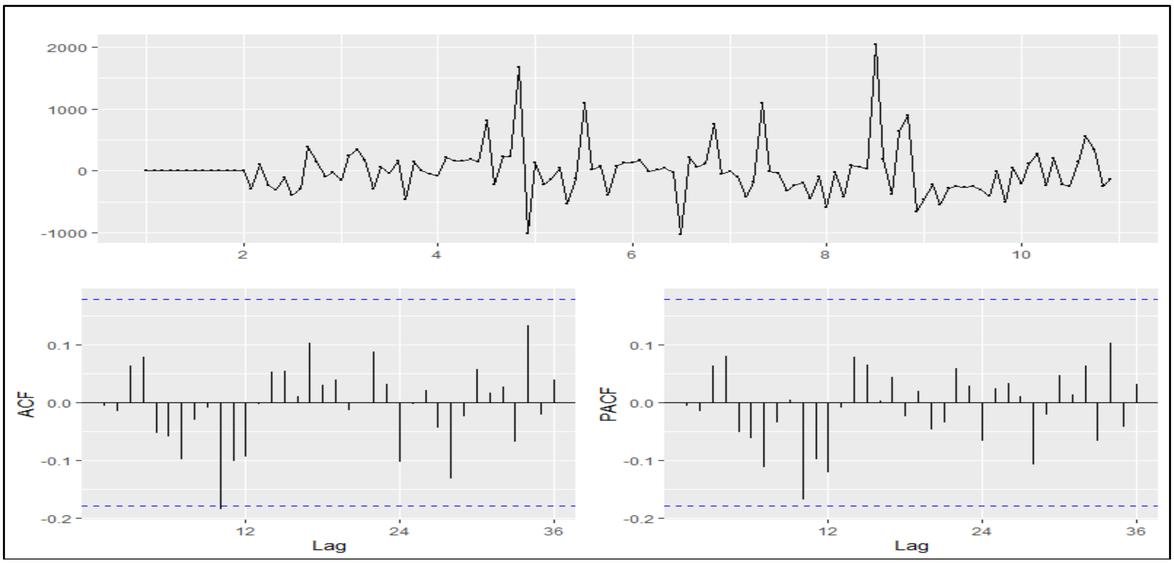

Fig. 2. Plots of standardized residuals of ARMA (2,1)-GARCH (1,1) model

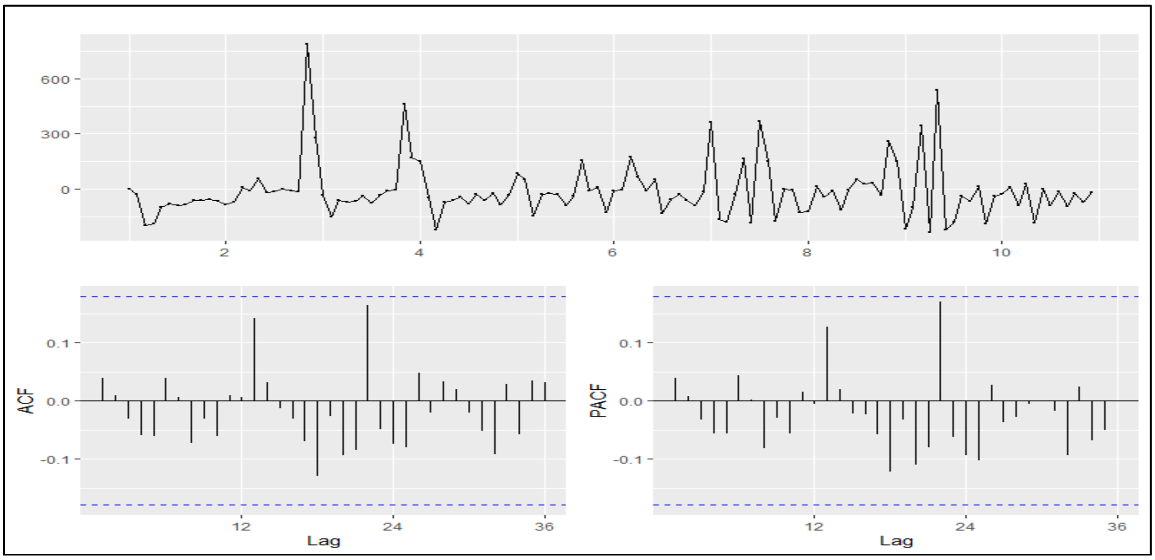

Fig. 3. Plots of standardized residuals of ARMA (2,1)-EGARCH (1,1) model

Table 6. Diagnostic checking of ARMA (2,1)-GARCH (1,1) and ARMA (2,1)-EGARCH (1,1) Models with Student-t distribution

	ARMA (2,1) - GARCH (1,1) Model with Student-t			
	Ljung-box squared residual		**ARCH LM Test**	
	Statistics	**P-value**	**Statistics**	**P-value**
Lag [3]	0.14	0.70	0.02	0.87
Lag [5]	0.34	0.97	0.21	0.96
Lag [7]	0.51	0.99	0.26	0.99
	ARMA (2,1) - EGARCH (1,1) Model with Student-t			
Lag [3]	0.10	0.74	0.02	0.89
Lag [5]	0.25	0.98	0.14	0.97
Lag [7]	0.35	0.99	0.20	0.99

Table 7. Observed and Predicted of onion prices (Rs/Quintal) for India monthly average wholesale prices of onion for the year 2021 by ARMA-GARCH and ARMA-EGARCH models

Month	**Observed**	**ARMA (2,1) – GARCH (1,1)**		**ARMA (2,1)- EGARCH (1,1)**	
		Predicted	**RD (%)**	**Predicted**	**RD (%)**
Jan-21	3155.65	3502.23	-10.98	3375.53	-6.97
Feb-21	3663.68	3463.24	5.47	3463.45	5.47
March-21	2708.56	2800.25	-3.39	2526.15	6.73
April-21	1806.54	2003.23	-10.89	1947.89	-7.82
May-21	1812.64	1900.23	-4.83	1787.29	1.40
June-21	2120.73	1923.21	9.31	2283.27	-7.66
July-21	2337.94	2122.31	9.22	2222.38	4.94
August-21	2335.5	2224.15	4.77	2498.85	-6.99
Sept-21	2255.46	2154.26	4.49	2324.25	-3.05
Oct-21	3036.44	3212.78	-5.81	3185.88	-4.92
Nov-21	3224.9	3355.84	-4.06	3154.14	2.19
Dec-21	2851.67	2545.12	10.75	3000.12	-5.21

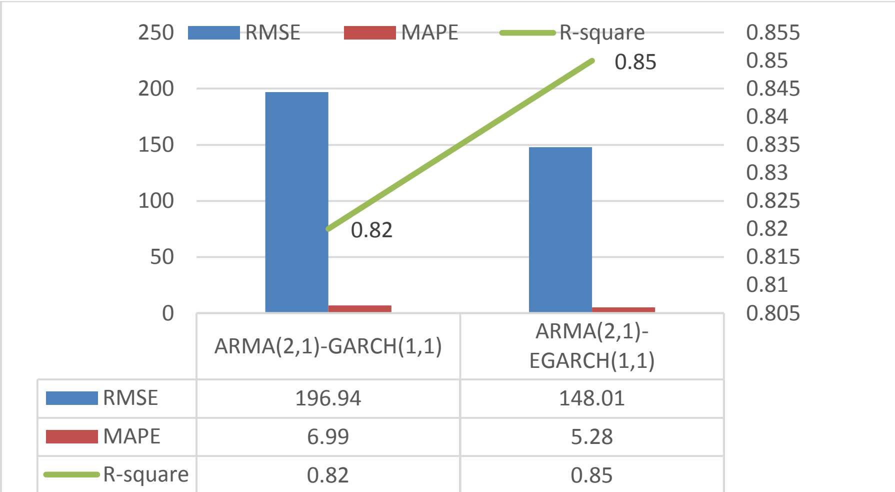

Fig. 4. Plots of RMSE, MAPE and R-square of ARMA (2,1)-GARCH (1,1) and ARMA (2,1)-EGARCH (1,1) models

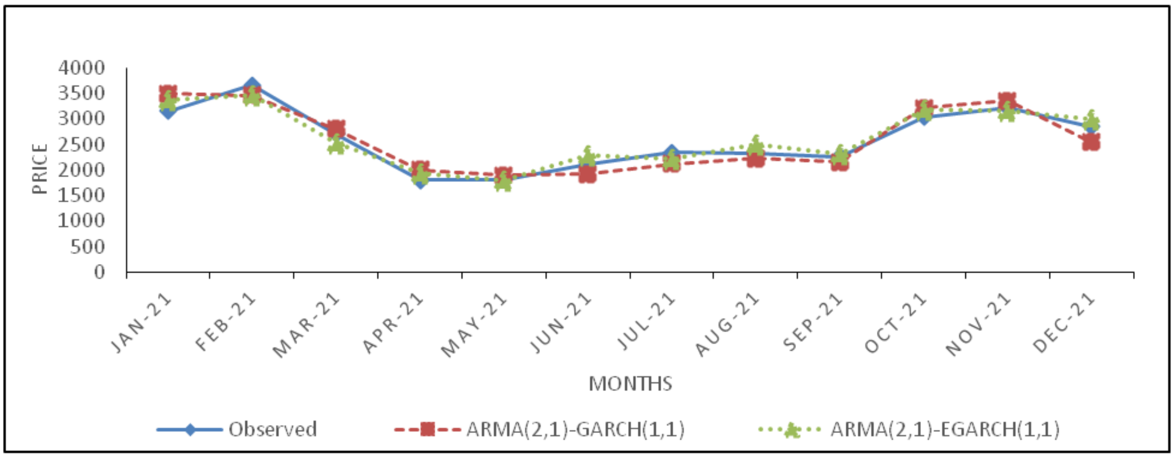

Fig. 5. Plot of observed and predicted India monthly average wholesale prices (Rs/Quintal) of onion for the year 2021 by ARMA-GARCH and ARMA-EGARCH models

4.3 Forecasting Performance

The four statistical measures: Relative deviation percentage (RD%), RMSE (Root mean squared error) MAPE (mean absolute percentage error) and R-square are used to compare the volatility forecasting performance of selected ARMA (2,1)-GARCH (1,1) and ARMA (2,1)-EGARCH (1,1) models. Relative deviation percentage (RD%) of these selected models is shown in Table 7. The corresponding plot of observed and predicted values from selected models is given in Fig. 5. ARMA (2,1)-EGARCH (1,1) model is selected as appropriate volatility forecasting model on base of smaller values RMSE (148.01) and MAPE (5.28) of ARMA (2,1)-EGARCH (1,1) model as compare to RMSE (196.94) and MAPE (6.99) ARMA (2,1)-GARCH (1,1) model while R-square (0.85) of ARMA (2,1)-EGARCH (1,1) is higher than R-square (0.82) of ARMA (2,1)-GARCH (1,1) model are shown in Fig. 4.

5. CONCLUSION

The study utilized all India monthly average wholesale prices of onion over period Jan-2010 to Dec-2021 and employed ARMA-GARCH, ARMA-EGARCH and ARMA-TGARCH models with different error distribution such as normal and student-t. ARMA (2,1) model was the best fitted model in the mean equation for the log returns on the basis of least value AIC and BIC, whereas in the variance equation, basic GARCH (1,1) and EGARCH (1,1) models with student-t innovations are appropriate in describing the symmetric and asymmetric behaviours of the log returns respectively. ARMA (2,1)-EGARCH (1,1) models selected as appropriate volatility forecasting model for all India monthly average wholesale prices of onion on the basis of smaller values of statistical measures such as RD(%), RMSE and MAPE, and higher value of R-square.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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