International Journal of Bio-resource and Stress Management https://ojs.pphouse.org/index.php/IJBSM

Crossref

IJBSM October 2025, 16(10): 01-06

Article AR6124

Research Article

Natural Resource Management

DOI: HTTPS://DOI.ORG/10.23910/1.2025.6124

Forecasting of Onion Price through GARCH and EGARCH Time Series Models in Nasik District of Maharashtra

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0009-0007-5188-0764

ABSTRACT

The experiment was conducted from March, 2023 to March, 2024 at Dr. RPCAU, Pusa, Bihar, India to study the performance of GARCH and EGARCH models for forecasting onion prices. The study was based on secondary data on onion prices taken from Agmarket, Indiastat, and other websites. Data on modal prices was collected from January 2011 to March 2024. The study employed Generalized Autoregressive Conditional Heteroskedasticity (GARCH) and Exponential GARCH (EGARCH) models to forecast onion prices in the Nasik district of Maharashtra, addressing price fluctuations that affected farmers and consumers. Weekly onion price data from January 2011 to March 2024 was reviewed to identify volatility and trends. After differencing, the ADF test verified stationarity, and the ARCH-LM test confirmed the existence of volatility clustering. Asymmetric volatility was captured by the EGARCH model, while symmetric volatility was captured by the GARCH model. Model performance was assessed using AIC, BIC, and error measures such as MSE, MAE, and MAPE. The GARCH model performed better than the EGARCH model in predicting onion prices, according to the results, which showed lower error metrics with MSE, MAE, and MAPE values of 68,771.29, 208.59, and 15.91%, respectively. EGARCH, however, provided important insights into asymmetric price volatility, wherein price swings were more affected by positive shocks than by negative ones. This study highlighted GARCH's efficiency for short-term price forecasting and EGARCH's utility in understanding complex market behavior. The findings supported robust statistical approaches to managing price volatility, aiding farmers and policymakers in mitigating market risks.

KEYWORDS: GARCH, EGARCH, price volatility, statistical forecasting, onion prices

Citation* (VANCOUVER)*: Raju and Kumar, Forecasting of Onion Price through GARCH and EGARCH Time Series Models in Nasik District of Maharashtra. *International Journal of Bio-resource and Stress Management,* 2025; 16(10), 01-06. HTTPS://DOI.ORG/10.23910/1.2025.6124.

Data Availability Statement: Legal restrictions are imposed on the public sharing of raw data. However, authors have full right to transfer or share the data in raw form upon request subject to either meeting the conditions of the original consents and the original research study. Further, access of data needs to meet whether the user complies with the ethical and legal obligations as data controllers to allow for secondary use of the data outside of the original study.

Conflict of interests: The authors have declared that no conflict of interest exists.

RECEIVED on 05th February 2025 RECEIVED in revised form on 27th September 2025 ACCEPTED in final form on 08th October 2025 PUBLISHED on 30th October 2025

1. INTRODUCTION

Accurate price forecasting is crucial for market stability, especially for perishable crops like onions, which face significant price swings. Volatility affects farmers' income, food security, and economic stability. Efficient forecasting aids market predictions, supply chain management, and policy decisions. Price volatility of staple items complicates forecasting due to inconsistent residual conditional variance Jannah et al. (2021). While traditional models focus on conditional moments, ARCH and GARCH account for conditional variance. Engle (1982) introduced ARCH to capture time-varying variance, unlike earlier models assuming constant variance.

Time series analysis, which finds patterns and trends in past data, is essential for predicting agricultural prices. Particularly well-known for their capacity to simulate and predict the volatility present in price series are the statistical models GARCH (Generalized Autoregressive Conditional Heteroscedasticity) and EGARCH (Exponential GARCH). By taking into consideration time-varying conditional variance, GARCH models which were first proposed by Bollerslev in 1986 extend the ARCH framework and improve the depiction of volatility clustering, a prevalent feature in agricultural pricing data. The asymmetry in volatility reactions to positive and negative shocks, which is frequently seen in real-world data, is, however, limited by the symmetric character of GARCH models. Initially designed for financial markets, GARCH models are increasingly used in agriculture due to price fluctuations, with speculative hoarding causing agricultural prices to react more to positive than negative news (Thiyagarajan et al., 2015). Nelson (1991), who developed the EGARCH model to better manage asymmetric volatility, brought attention to this short coming. The effectiveness of the GARCH and EGARCH models in predicting the volatility of agricultural commodity prices has been shown in numerous research. In their investigation of the volatility of export data for fruit and vegetable seeds in India, Ghosh and Paul (2010) used these models and discovered that EGARCH performed better than GARCH at identifying asymmetric volatility patterns. Similarly, Bhardwaj et al. (2014) highlighted that when it comes to managing volatility in the daily price data of grams, GARCH models outperform conventional ARIMA models. Bansal and Zala (2023) analyzed Castor price volatility using ARCH and GARCH. Lama et al. (2015) highlighted EGARCH's effectiveness for cotton price indices. Kumar et al. (2021) found ARMA-GARCH provided realistic onion price forecasts. Abebe et al. (2022) showed GARCH-MIDAS improved commodity volatility forecasting in ECX. Pushpa et al. (2022) demonstrated GARCH (1,1) and EGARCH (1,1) effectively captured onion price dynamics based on lower AIC and BIC. Additionally, Rakshit et al. (2023) demonstrated how well EGARCH models worked to explain asymmetric price volatility for perishable goods like potatoes, when negative shocks outweighed positive ones.

Furthermore, research by Pramanik and Alam (2023) and Alam et al. (2013) has confirmed that GARCH models are reliable in capturing the volatility dynamics of agricultural prices. Pramanik and Alam showed that GARCH models performed better than ARIMA in predicting onion prices in the Kolhapur market, while Alam et al. (2013) observed that GARCH and EGARCH models were appropriate for simulating the daily price volatility of agricultural indices.

EGARCH offers more flexibility by modelling asymmetry, which makes it especially helpful for commodities with erratic pricing patterns, even if GARCH is well-suited for capturing symmetric volatility. This contrast emphasizes how crucial it is to use the right model depending on the underlying data structure in order to produce the most accurate forecasts. Reddy et al. (2023) and Reddy et al. (2021) used MAE, MAPE, and RMSE to evaluate price forecasting models for cotton and turmeric, respectively. The study provides a localized perspective on volatility modelling and its useful applications by concentrating on the Nasik area. This study was aimed to predict onion prices in Nasik, Maharashtra, using GARCH and EGARCH models on over a decade of weekly data, aiming to compare their performance in a volatile market.

2. MATERIALS AND METHODS

The experiment was conducted during March, 2023 to March, 2024 at Dr. Rajendra Prasad Central Agricultural University (RPCAU) in Pusa, Samastipur, Bihar, located at 25.98°N latitude and 85.67°E longitude during 2024.

2.1. Study area and data collection

This study focuses on the Nasik district of Maharashtra, one of the largest onion-producing regions in India. Weekly onion price data has been extracted from the AGMARKNET website. The dataset contains 691 observations for analysis and covers the period from the first week of January 2011 to the last week of March 2024. The region's substantial contribution to onion production and the availability of trustworthy long-term price records served as the basis for choosing the study area and dataset.

2.2. Data preprocessing

To ensure consistency, the obtained data on prices was pre-processed. Interpolation methods were used to deal with missing values. To stabilize variance, logarithmic transformations were used. The Augmented Dickey-Fuller

(ADF) test was used to assess the price series' stationarity. While the alternative hypothesis verified stationarity, the null hypothesis examined whether the series had a unit root (non-stationary). In time series analysis, stationarity is essential because it ensures the independence of data points, which is a necessary condition for the majority of forecasting models to correctly identify and forecast future trends (Pramanik and Alam, 2023).

2.3. *GARCH model specification*

Time-varying conditional variance was captured using the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model, which was created by Bollerslev (1986). The following is the GARCH (1,1) model's conditional variance equation:

$$\omega+\alpha\varepsilon_{t-1}^{2}+\beta\sigma_{t-1}^{2} \qquad \text{....(i)}$$

where, σ_t^2 is the conditional variance, ω is a constant, α represents the impact of past squared residuals (ARCH effect) and β represents the lagged conditional variance (GARCH effect).

2.4. *EGARCH model specification*

Nelson (1991) developed the Exponential GARCH (EGARCH) model, which takes into consideration the asymmetric effects of both positive and negative shocks. The following is its conditional variance equation:

$$ln(h_t)=a_0+\beta\ \ln(h_{t-1})+\alpha|\varepsilon_{t-1}/\sqrt{h_{t-1}}|+\gamma\varepsilon_{t-1}/\sqrt{h_{t-1}} \qquad \text{....(ii)}$$

Where *ln* indicates natural logarithm & $h_t=\sigma_t^2$.

This model works well with datasets that exhibit asymmetric volatility patterns as it ensures non-negative variance and accounts for leverage effects.

2.5. *Model estimation*

We used Maximum Likelihood Estimation (MLE) to estimate both models. To find autocorrelation in squared residuals, we used the Ljung-Box Q-Test and ARCH-LM test to verify whether ARCH effects are present. Bayesian Information Criterion (BIC) and the Akaike Information Criterion (AIC) were used to compare the models' performances. The forecasting accuracy was assessed using the MSE, MAE, and MAPE error measures.

Out-of-sample forecasting was conducted for the last 12 weeks (680th to 691st week). Insights into price volatility patterns were obtained by comparing the model estimates with actual prices. The steps taken include- Data preparation and Stationarity check, Model specification, Diagnostic checks and Performance evaluation, and Final forecasting and Result analysis.

3. RESULTS AND DISCUSSION

3.1. *Descriptive Statistics*

Descriptive statistics of the weekly onion price data were given in Table 1. A standard deviation of ₹ 1057.88 and a coefficient of variation of 71.46% indicated substantial volatility in the onion price data, which revealed a mean price of ₹ 1480.47 q^{-1}. With prices ranging from ₹ 284.00 to ₹ 6700.75 q^{-1}, the market was positively skewed (1.74) and leptokurtic (6.58), suggesting dramatic swings and sporadic spikes. Figure 1 showed the actual weekly onion price series, whereas in Figure 2, the volatility of prices could be observed. The stationarity of the time series data used for the study was tested using the Augmented Dickey-Fuller unit root test, as indicated in Table 2. At a significance threshold of five percent, the time series was found to be stationary. The null hypothesis that the series had a unit root was strongly rejected due to the low p-value. Table 3 demonstrated that the ARCH LM test rejected the null hypothesis of constant variance by indicating strong ARCH effects in the time series. This supported the use of

Table 1: Descriptive statistics of onion price

Lag order	Statistic
Mean (₹ q^{-1})	1480.47
Standard Deviation (₹ q^{-1})	1057.88
Kurtosis	6.58
Skewness	1.74
Minimum (₹ q^{-1})	284.00
Maximum (₹ q^{-1})	6700.75
CV %	71.46

Table 2: Unit root test for onion price series

Series	Lag Order	ADF	
		Statistic	*p-value*
Level	8	-5.089	0.01**

**p-value implies strong evidence against the null hypothesis of a unit root, i.e., series is stationary at a 1% significance level

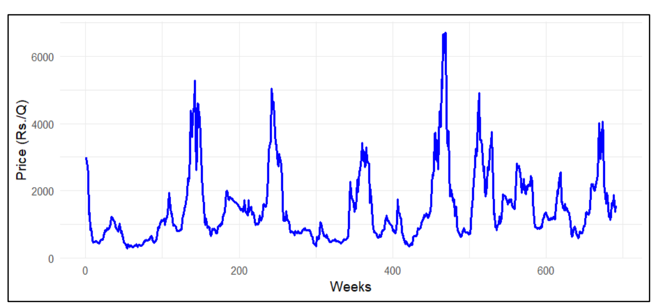

Figure 1: Actual weekly onion price series

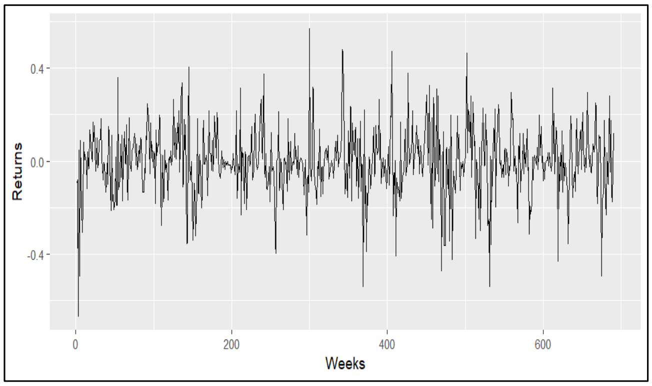

Figure 2: Volatility in onion price series

Table 3: Result of ARCH-LM test of onion price series

Lag Order	Statistic	*p*-value
12	571.77	<2.2e-16**

**p-value implying that there is highly significant evidence of ARCH effects in the time series data at a 1% level of significance

GARCH models to capture and forecast volatility dynamics by confirming time-varying volatility.

3.2. *GARCH model specifications*

The GARCH (1,1) model exhibited substantial parameters, as indicated in Table 4, with historical errors (MA1=0.239) and previous prices (AR1 = 0.989) having had a considerable impact on current prices. The strong volatility persistence ($\alpha+\beta=0.999$) suggested that the impacts of volatility shocks lasted for a long time. The log-likelihood indicated that the model fitted well (-4623.095).

The model could be represented as,

Mean equation:

$$Price_t = 2045.833 + (0.989 \times Price_{t-1}) + (0.239 \times \varepsilon_{t-1}) + (\varepsilon_t) \quad ......(i)$$

Variance equation:

$$\sigma_t^2 = 2711.508 + (0.411 \times \varepsilon_{t-1}) + (0.588 \times \sigma_{t-1}^2) \quad ......(ii)$$

Forecasting equation:

To forecast the price level:

$$Price_{t+1} = 2045.833 + (0.989 \times Price_t) + (0.239 \times \varepsilon_t) \quad ......(iii)$$

To forecast the volatility:

$$\sigma_t^2 = 2711.508 + (0.411 \times \varepsilon_t^2) + (0.588 \times \sigma_t^2) \quad ......(iv)$$

The price at a given time was dependent on previous prices, residuals, and new shocks, as shown by equations (i) and (ii). In contrast, the variance at that time depended on conditional variance and previous squared residuals. The price level and volatility for the subsequent period were predicted by equations (iii) and (iv), where the variance equation modeled volatility and the mean equation captured price dynamics.

Table 4: Parameter estimates of GARCH for onion price series

GARCH (1,1)				
Parameter	Estimate	Std. Error	t-value	*p*-value
μ	2045.833	266.684	7.671	<0.001
ar1	0.989	0.006	169.421	<0.001
ma1	0.239	0.045	5.357	<0.001
ω	2711.508	450.702	6.016	<0.001
α	0.411	0.042	9.800	<0.001
β	0.588	0.027	21.875	<0.001
Log-likelihood	-4623.095			

3.2.1. *News impact curve (NIC) of GARCH (1,1)*

The GARCH model's News Impact Curve (Figure 3) was symmetric, meaning that volatility was equally affected by positive and negative shocks of the same size. This suggested that the model treated all shocks according to size rather than direction, which restricted its capacity to account for asymmetric impacts, in which volatility was frequently more affected by bad news (negative shocks) as observed in many financial markets.

3.3. *EGARCH model specifications*

Table 5 demonstrated that the EGARCH (1,1) model exhibited substantial persistence in both price and volatility dynamics. The model also showed asymmetric volatility responses, with positive shocks raising volatility more than negative ones. The ARMA (1,1) structure emphasized reliance on past values and shocks. This demonstrated how returns responded differently to market shocks due to the leverage effect. The mean and variance behaviour of the data were robustly described by the model, which also showed a good fit.

Table 5: Parameter estimates of EGARCH for onion price series

EGARCH (1,1)				
Parameter	Estimate	Std. Error	t-value	*p*-value
μ	2153.399	213.293	10.096	<0.001
ar1	0.975	0.003	296.941	<0.001
ma1	0.189	0.040	4.731	<0.001
ω	0.869	0.009	91.873	<0.001
α	0.331	0.022	14.947	<0.001
β	0.921	0.001	1335.075	<0.001
γ	0.295	0.066	4.478	<0.001
Log-likelihood	-4580.545			

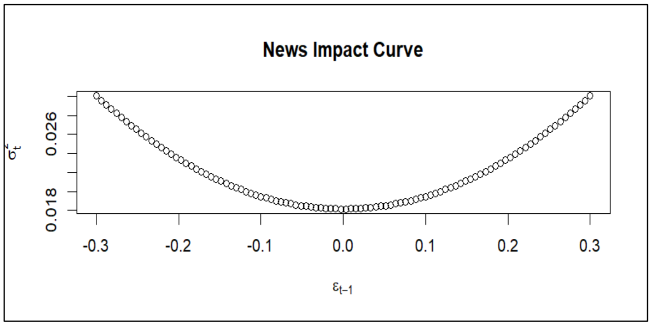

Figure 3: Symmetric GARCH news impact curve of onion price series

The model could be represented as,

Mean equation:

$r_t=2153.339+(0.975r_{t-1})+\varepsilon_t+(0.189\times\varepsilon_{t-1})$ ......(v)

Volatility equation:

$Log(\sigma_t^2)=0.869+0.921\log(\sigma_{t-1}^2)+(0.331z_{t-1})+(0.295z_{t-1})$..(vi)

Forecasting equation:

For forecasting the next period's volatility σ_{t+1}^2:

$Log(\sigma_{t+1}^2)=0.869+0.921\log(\sigma_t^2)+(0.331z_t)+(0.295z_t)$ ....(vii)

To forecast the next return (r_{t+1}):

$r_{t+1}=2153.339+(0.975r_t)+\varepsilon_{t+1}+(0.189\times\varepsilon_t)$ ......(viii)

Equation (v) explained how past returns and errors affected the price/return at time t, while equation (vi) modeled the volatility dynamics over time t, and equations (vii) and (viii) were used for volatility and return forecasting based on the fitted EGARCH (1,1) model.

3.3.1. News impact curve (NIC) of EGARCH (1,1)

The News Impact Curve of the onion price series (Figure 4) exhibited a reversal asymmetry, where positive price shocks led to larger increases in volatility compared to negative shocks. This behavior was reflected in the positive γ parameter (0.295) of the EGARCH (1,1) model, indicating that upward shocks (good news) triggered stronger volatility responses, in contrast to many financial markets where negative shocks typically dominated. The α (0.331) and β (0.921) parameters further confirmed that larger shocks amplified volatility and that volatility remained persistent following a shock. The model effectively captured this asymmetric volatility, which was likely driven by inflationary pressures or supply constraints in the onion market.

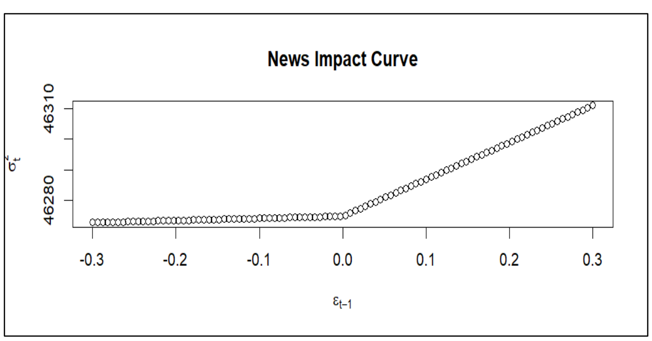

Figure 4: Asymmetric EGARCH news impact curve of onion price series

3.4. Model comparison

Tables 6 and 7 intricated the model's performance based on the information criteria and error metrics, which suggested that, according to the AIC and BIC values, the EGARCH model outperformed the GARCH model with a very slight difference in values, while the lowest values of MSE, MAE, and MAPE showed that the GARCH model was the best fit.

Table 6: Information criteria of GARCH & EGARCH model

Criteria	GARCH	EGARCH
AIC	13.398	13.278
BIC	13.438	13.324

Table 7: Error metrics for GARCH & EGARCH models

Validation criteria	For trained model		For test model	
Variety	GARCH	EGARCH	GARCH	EGARCH
MSE	99431.290	97280.270	68771.290	77139.540
MAE	176.230	176.951	208.594	230.472
MAPE	10.744	11.227	15.905	17.504

The results of price forecasting using the GARCH model were consistent with the findings of previous studies, including those by Pramanik and Alam (2023), Mahmoud (2023), Kumar et al. (2021), Bharadwaj et al. (2014), Alam et al. (2013), and Yaziz et al. (2011). Similarly, the ability of the EGARCH model to capture asymmetric volatility aligned with the results reported by Ghosh and Paul (2010), Lama et al. (2015), and Pushpa et al. (2022), and Dessie et al. (2023).

4. CONCLUSION

The GARCH and EGARCH models fitted the data well, with all parameters statistically significant. While GARCH captured symmetric volatility, EGARCH displayed asymmetric responses, with News Impact Curves showing a stronger reaction to positive shocks. Despite similar AIC and BIC values, GARCH outperformed

EGARCH in forecasting accuracy, with a lower MAPE (15.905 vs. 17.504). Thus, GARCH remains more effective for forecasting onion prices, though EGARCH offers insights into volatility asymmetry.

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