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Asymmetric Price Volatility of Onion in India

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ABSTRACT

Price of onion shows a high degree of volatility. Price volatility is said to be asymmetric when it is affected by positive and negative shocks of same magnitude with different degree. Asymmetric volatility can be captured by asymmetric GARCH type of model such as EGARCH, APARCH and GJR-GARCH. Weekly modal price of onion for Delhi, Lasalgaon and Bengaluru markets are modelled with the help of these asymmetric variance models. For the present investigation, APARCH model outperformed the other competing models and it is considered as the best fit model for the data under consideration. Finally, the extent of asymmetry due to positive and negative shocks for all these markets are visualised with the help of News Impact Curves.

Keywords: APARCH, EGARCH, GARCH, GJRGARCH, News Impact Curve.

JEL: D82, Q11, Q18

I

INTRODUCTION

Onion is one of the very important vegetables in India. It is almost a necessary component for the Indian diet. It is the most produced vegetable in India (23.49 MT, 3rd Advance Estimate, 2018-19) after potato. India is the second largest producer of onion in the world next after China. The onion growing areas are not homogeneously spread across the length and breadth of India. Major onion growing states are Maharashtra, Karnataka, Gujarat, Madhya Pradesh and Bihar. It is grown in more than one season. Its supply chain is highly affected by external shocks like weather abnormalities and policy regulations. High perishability and paucity of modern cold storage system are also constraints of uninterrupted supply chain. Onion price exhibits a high degree of price volatility. Among the three most price sensitive vegetables, namely, tomato, onion and potato, it also exhibits the highest instability index (49.30 per cent) during 2011-16 (Saxena *et al.,* 2017).

Price volatility prediction is important for all the stakeholders present within the supply chain. Price spike has been observed in each alternate year since 2013. The highest ever price spike has been observed in the end of 2019 across the country. The major wholesale markets of onion can be grouped into producers’ markets if they belong in major onion producing states and the metropolitan cities can be considered

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as consumers' markets. Murthy and Subrahmanyam (2003) studied the demand and supply analysis of onion under uncertain production situations. Chengappa *et al*. (2012) studied the competitiveness of major onion markets in Karnataka and Maharashtra. Saxena *et al.* (2020) studied that how price shocks are transmitted from the consumers' markets to producers' markets.

Autoregressive Conditional Heteroscedastic (ARCH) (Engle, 1982) and Generalized ARCH (GARCH) (Bollerslev, 1986) models are used as variance model to capture volatility along with Autoregressive Integrated Moving Average (ARIMA) methodology (Box et al., 2016) as mean model. A lot of application of GARCH model have been found to address the volatilities in Indian agricultural scenario. Paul *et al.* (2009) applied GARCH model for forecasting India's Volatile Spices Export. Paul *et al.* (2014) studied ARIMAX (ARIMA with exogenous variable)-GARCH model and developed out of sample forecast formulae. Paul *et al*. (2015a) investigated food price volatility in India using GARCH model. Paul (2015) proposed algorithm for combination of ARIMAX, GARCH and Wavelet for forecasting time series. Paul *et al*. (2015b) analysed presence of structural breaks in onion price volatility and found the significant break in the years 2007, 2010, 2011 and 2013, when onion prices went abnormally high and created disturbances in the markets.

Although the ARCH and GARCH models are very much popular, they do not take into account the asymmetry in the volatility. That is, the positive and negative shocks of equal strength may lead to different responses to the volatility in some time series data. To overcome this limitation various asymmetric GARCH type of models have been evolved subsequently such as Exponential GARCH (EGARCH) (Nelson, 1991), Asymmetric Power ARCH (APARCH) (Ding *et al*., 1993) and GJR-GARCH (Golsten *et al.,* 1993). Applications of GARCH and EGARCH models have also been found in agricultural time series data (Ghosh *et al*., 2010). Paul et al. (2019) investigated different multivariate GARCH models for explaining volatility and spillover in onion prices in major markets of Karnataka, India. Paul et al. (2016) notified asymmetric price volatility of onion at different markets of Delhi using EGARCH model. They demonstrated that EGARCH model could be efficiently used for capturing asymmetric price volatility in onion in selected markets of Delhi, Indian. In the present investigation, an attempt has been made to study the asymmetric volatility in onion prices in major markets of India. Also extent of asymmetry is observed with the help of News Impact Curve (NIC).

II

SOME THEORETICAL ASPECTS

The ARCH and GARCH Model

Linear models like ARIMA are not able to describe any changes in the conditional variances present in real data because of its assumption of homoscedasticity in the error variance. To overcome this situation Engle (1982) proposed the ARCH model by considering significant autocorrelations in the squared residual series.

The process $\{\varepsilon_t\}$is said to have ARCH (q) if the conditional distribution of $\{\varepsilon_t\}$ given the available information(ψ_{t-1}) upto $t-1$ time period is represented as:

$$\varepsilon_t|\psi_{t-1} \sim N(0, h_t) \; and \; \varepsilon_t = \sqrt{h_t}v_t \qquad \text{…. (1)}$$

where $v_t$is independently and identically distributed (IID) with zero mean and unit variance. This is known as innovation. The distribution of innovation varies according to the time series data. Generally, it is assumed that the innovation follows normal distribution. While in the presence of excess kurtosis, Student *t*-distribution or Generalized Error Distribution (GED) can be used as an alternative one.

The conditional variance h_t is calculated as

$$h_t = a_0 + \sum_{i=1}^{q} a_i \varepsilon_{t-i}^2 \, , a_0 > 0, a_i \geq 0 \; \forall \; i \; and \;\; \sum_{i=1}^{q} a_i < 1 \qquad \text{…. (2)}$$

But the ARCH models give satisfactory forecast only with a large number of parameters which has necessitated the emergence of more parsimonious version, i.e. the generalised ARCH (GARCH) models (Bollerslev, 1986). In GARCH model, the conditional variance is considered as a linear function of its own lags also. The GARCH (*p,q*) process has the following form of conditional variance

$$h_t = a_0 + \sum_{i=1}^{q} a_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} b_j h_{t-j}$$

provided $a_0 > 0, a_i \geq 0 \; \forall \; i, b_j \geq 0 \; \forall \; j$ …. (3)

a_i and b_j are the measures of how the current volatility is affected by earlier shocks and volatilities respectively. The GARCH (*p,q*) process is said to be weak stationary if and only if

$$\sum_{i=1}^{q} a_i + \sum_{j=1}^{p} b_j < 1 \qquad \text{…. (4)}$$

For GARCH (1,1) model conditional variance h_t is reduced to

$$h_t = a_0 + a_1 \varepsilon_{t-1}^2 + b_1 h_{t-1} \qquad \text{…. (5)}$$

GARCH model considers that the effect of volatility is dependent of magnitude of the shocks only and invariant of the sign of shocks. And it cannot capture the asymmetric volatility as it ignores the correlation between volatility and sign of the shocks. To overcome the problem of capturing the asymmetric volatility of a time series data, various asymmetric GARCH type of models has been developed, namely, EGARCH, APARCH and GJR-GARCH.

Exponential GARCH (EGARCH)

To capture the asymmetric volatility of a time series dataset the first introduced asymmetric GARCH type of model is EGARCH model (Nelson, 1991). This model not only describes the asymmetry on the volatility, but also has the advantage that the positivity of the conditional variance is always attained without imposing any restriction on the parameters unlike GARCH model since it is defined in terms of the logarithm function. The conditional variance for EGARCH model has following form,

$$\ln h_t = a_0 + \sum_{j=1}^{p} b_j \ln h_{t-j} + \sum_{i=1}^{q} \left(a_i \left| \frac{\varepsilon_{t-i}}{\sqrt{h_{t-i}}} \right| + \gamma_i \frac{\varepsilon_{t-i}}{\sqrt{h_{t-i}}} \right) \quad \text{.... (6)}$$

The asymmetric factor γ_i denotes the asymmetric effect to different shocks. $\gamma_i = 0$ indicates a symmetric condition where both the positive and negative shock of same magnitude have equal effect on volatility. The positive shocks have more impact on volatility than the negative shocks if $\gamma_i > 0$, while the opposite situation occurs if $\gamma_i < 0$.For EGARCH (1,1) model conditional variance h_t is reduced to

$$\ln h_t = a_0 + b_1 \ln h_{t-1} + \left(a_1 \left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right| + \gamma_1 \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right) \quad \text{.... (7)}$$

GJR-GARCH

Glosten *et al.* (1993) proposed GJR-GARCH model by considering the fact that impact of ε_{t-1}^2 on the conditional variance depends on the sign of ε_{t-1}. An indicator variable is introduced to capture the sign dependency. Here the conditional variance is defined as

$$h_t = a_0 + \sum_{j=1}^{p} b_j h_{t-j} + \sum_{i=1}^{q} a_i \varepsilon_{t-i}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1} \quad \text{.... (8)}$$

where $\gamma(-1 \leq \gamma \leq 1)$ is the asymmetric parameter and I_{t-1} is the indicator variable, such that :

$$I_{t-1} = 1 \quad if\ \varepsilon_{t-1} < 0$$
$$\qquad 0 \quad if\ \varepsilon_{t-1} \geq 0$$

For GJR-GARCH (1,1) model conditional variance h_t is reduced to

$$h_t = a_0 + a_1 \varepsilon_{t-1}^2 + b_1 h_{t-1} + \gamma \varepsilon_{t-1}^2 I_{t-1} \qquad \text{.... (9)}$$

Asymmetric Power ARCH (APARCH)

Ding *et al*. (1993) introduced APARCH model by considering some asymmetric power to the conditional variance h_t. The conditional variance has following form for this model

$$h_t^{\frac{\delta}{2}} = a_0 + \sum_{j=1}^{p} b_j h_{t-j}^{\frac{\delta}{2}} + \sum_{i=1}^{q} a_i (|\varepsilon_{t-i}| - \gamma \varepsilon_{t-i})^{\delta} \qquad \text{.... (10)}$$

where $\gamma(-1 \le \gamma \le 1)$ is the parameter for asymmetry and $\delta(\ge 0)$ is the power term parameter. A lot of GARCH type models can be fitted within the APARCH model by considering some specific values to the parameters. By considering $\delta = 2$ and $\gamma = 0$, it will be same as GARCH model. For APARCH (1,1) model conditional variance h_t is reduced to

$$h_t^{\frac{\delta}{2}} = a_0 + b_1 h_{t-1}^{\frac{\delta}{2}} + a_1 (|\varepsilon_{t-1}| - \gamma \varepsilon_{t-1})^{\delta} \qquad \text{.... (11)}$$

ARCH-In-Mean

It has been observed that an asset with a higher perceived risk would pay a higher return on average. To capture this phenomena Engle *et al*. (1987) introduced ARCH-in-mean or ARCH-M model by including conditional variance as a regressor in the mean model. For any financial time series $\{y_t\}$ ARCH-in-mean or ARCH-M model has following form:

$$y_t = \mu + \lambda h_t + \varepsilon_t \qquad \text{.... (12)}$$

where, ε_t is an ARCH process. λ is the volatility compensation parameter that can describe the effect that higher perceived variability of ε_t has on the level of y_t and μ is the mean return. When ε_t follows a GARCH process then it is said to be a GARCH-in-mean, or GARCH-M model. In this paper all the asymmetric variance models are also considered with their in-mean specification.

The News Impact Curve (NIC)

The News Impact Curve (Engle and Ng, 1993) measures how volatility is affected by new information. This curve is named as NIC because it reflects past return shocks to current volatility. NIC highlights the implicit relationship between

ε_{t-1} and h_t. It is considered that all the information before $t-1$ time periods are constant and all lagged conditional variances are represented by the numerical level of the unconditional variance.

The conditional variance equation of any parametric GARCH type of model can be bifurcated as

$$f(h_t) = f(I) + \eta(\varepsilon_{t-1}, \varepsilon_{t-2}, \varepsilon_{t-3}, \dots, \varepsilon_{t-q}) \qquad \dots. (13)$$

where η (ε_{t-1}, ε_{t-2}, ε_{t-3}, ..., ε_{t-q}) is a function depends upon ε_{t-1} and *f (I)* is independent of ε_{t-1}. As an assumption is imposed that all the information before $t-1$ time periods are constant, the conditional variance equation can be written as

$$f(h_t) = f(I) + \eta(\varepsilon_{t-1}) \qquad \dots. (14)$$

Now, NIC is defined as

$$f(h_t) = \eta(\varepsilon_{t-1}) \qquad \dots. (15)$$

For the GARCH model, the NIC is a symmetric curve with the quadratic function and the line of symmetry is $\varepsilon_{t-1} = 0$. This can be justified as positive and negative shock of same magnitude have equal effect on volatility. But in case of any other asymmetric GARCH type of model, the NIC is an asymmetric curve. The equation for NIC for the GARCH (l, 1) model is

$$h_t = \alpha_1 \varepsilon_{t-1}^2 \qquad \dots. (16)$$

For EGARCH (1,1) model, estimating the lagged conditional variance h_{t-1} at the numerical level of the unconditional variance σ, the equations for NICs are

$$\ln h_t = \left(\frac{\gamma_1 + \alpha_1}{\sigma}\right)\varepsilon_{t-1}, \text{ for } \varepsilon_{t-1} > 0$$
$$\ln h_t = \left(\frac{\gamma_1 - \alpha_1}{\sigma}\right)\varepsilon_{t-1}, \text{ for } \varepsilon_{t-1} < 0 \qquad \dots. (17)$$

For GJRGARCH (1,1) model, the equations for NICs are

$$h_t = \alpha_1 \varepsilon_{t-1}^2, \text{ for } \varepsilon_{t-1} > 0$$
$$h_t = (\alpha_1 + \gamma)\varepsilon_{t-1}^2, \text{ for } \varepsilon_{t-1} < 0 \qquad \dots. (18)$$

And for APARCH (1,1) model the equations for NICs are

$$h_t^{\frac{\delta}{2}} = \alpha_1 (1-\gamma)^{\delta} \varepsilon_{t-1}{}^{\delta}, \text{ for } \varepsilon_{t-1} > 0$$

$$h_t^{\frac{\delta}{2}} = a_1(1+\gamma)^{\delta}(-\varepsilon_{t-1})^{\delta}, \text{ for } \varepsilon_{t-1} < 0 \quad \text{.... (19)}$$

III

DATA AND METHODOLOGY

To conduct the study of asymmetric price volatility of onion three major wholesale markets are selected. Out of these three markets one is consumers' market (Delhi) and two are producers' markets, namely, Lasalgaon in Maharashtra and Bengaluru in Karnataka. Daily time series data for modal spot prices (Rs./qtl) of onion for these markets for the time period 1st January, 2008 to 30th November, 2020 are collected from Department of Agriculture, Cooperation & Farmers' Welfare, Ministry of Agriculture & Farmers' Welfare, Government of India (https://agmarknet.gov.in/PriceAndArrivals/CommodityDailyStateWise.aspx). Daily data is converted to weekly data by taking average of seven days data. As the square of price return is considered as the realisation of price volatility, all the analysis is done based on price return series. Price return $\{r_t\}$ is calculated for a financial time series $\{y_t\}$ as

$$r_t = \frac{y_t - y_{t-1}}{y_{t-1}} \quad \text{.... (20)}$$

Although there is seasonal effect on the price series, price return series is always devoid of any seasonality. The first 90 per cent observations are used for model building purpose and the rest 10 per cent observations are used as hold out set for model validation. At first, autocorrelation function (ACF) and partial autocorrelation function (PACF) are obtained to verify the statistical dependencies among consecutive observations. After ensuring the presence of statistical dependencies Autoregressive moving average (ARMA) model with possible orders are fitted to the return series. After fitting the mean model residuals are obtained. The residuals are tested using ARCH-LM test for the presence of heteroscedasticity. After confirming the presence of heteroscedasticity in residual series, GARCH-M, EGARCH-M, APARCH-M and GJR-GARCH-M models are fitted. The appropriate order of ARMA as a mean model for each variance model is chosen based on minimum information criteria such as Akaike Information Criterion (AIC), Bayesian information criterion (BIC) and Hannan–Quinn information criterion (HQC). AIC, BIC and HQC are defined as

$$AIC = -2\ln L + 2m \quad \text{.... (21)}$$

$$BIC = -2\ln L + m\ln n \quad \text{.... (22)}$$

and $HQC = -2\ln L + 2m\ln(\ln n)$ .... (23)

where, L is the likelihood, m is the total number of parameters to be estimated and n is the total number of observations. Finally the best fitted models for the three markets are obtained based on minimum Residual Sum of Square (RSS) (Sekhar *et al*., 2017), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) of the actual values and fitted values in the model building set. These evaluation criteria are calculated as

$$RSS = \sum_{t=1}^{T}(\varepsilon_t^2 - h_t)^2 \qquad \text{.... (24)}$$

$$RMSE = \left[\frac{1}{T}\sum_{t=1}^{T}(y_t - \hat{y}_t)^2\right]^{1/2} \qquad \text{.... (25)}$$

$$MAE = \frac{1}{T}\sum_{t=1}^{T}|y_t - \hat{y}_t| \qquad \text{.... (26)}$$

$$MAPE = \frac{1}{T}\sum_{t=1}^{T}\frac{|y_t - \hat{y}_t|}{y_t} \times 100 \qquad \text{.... (27)}$$

In the end, the extent of volatility asymmetry due to a positive and negative shock is visualised using NIC.

IV

RESULTS AND DISCUSSION

Descriptive statistics of the price and price return series are given in Table 1. Here, the total number of data points is 674 weeks. Bengaluru and Lasalgaon markets have the highest and lowest mean price respectively. The same trend has been followed for the minimum price. But Delhi exhibits the highest median price followed by Bengaluru and Lasalgaon markets. In terms of the maximum price, the Bengaluru market is far more than the Lasalgaon and Delhi markets. It is noticeable that all the three markets have a high degree of variation. Lasalgaon market has the highest coefficient of variation (CV) percentage followed by Bengaluru and Delhi.

TABLE 1. DESCRIPTIVE STATISTICS OF ONION PRICE AND PRICE RETURN SERIES FOR DELHI, LASALGAON AND BENGALURU MARKET

	Delhi		Lasalgaon		Bengaluru	
Statistics	Price	Price return	Price	Price return	Price	Price return
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Observations	674	673	674	673	674	673
Mean (Rs./q)	1300.66	0.01	1268.65	0.01	1308.16	0.01
Median	997.50	0.00	907.86	0.00	949.52	0.00
Minimum	300.00	-0.57	231.00	-0.48	319.05	-0.65
Maximum	6926.00	0.80	7129.00	0.98	11214.29	0.64
Standard deviation	924.13	0.12	1059.15	0.16	1085.24	0.14
CV (per cent)	71.05	1342.90	83.49	1064.42	82.96	1105.23
Skewness	2.22	1.04	2.16	1.15	3.41	0.46
Kurtosis	5.72	5.96	5.35	4.92	18.43	2.96

But the CV percentage for the price return series follows a different pattern. Here, the Delhi market has the highest CV percentage followed by Bengaluru and Lasalgaon markets. The price and price return series for all instances are positively skewed. The presence of leptokurtosis is seen in all cases and for the Bengaluru market price series, it is very high.

The time plot of price series and price return series for these markets is depicted in Figure 1 and Figure 2 respectively. From the time plot of the price series, a similar pattern has been seen for all three markets. The price spikes have been seen at the same periods for all of them. These price spikes occurred during 2010, 2013, 2017, 2019, and 2020. The highest ever price spike has been seen at the end of 2019. The plot of price return series indicates the relative change of prices with respect to the previous price realisation.

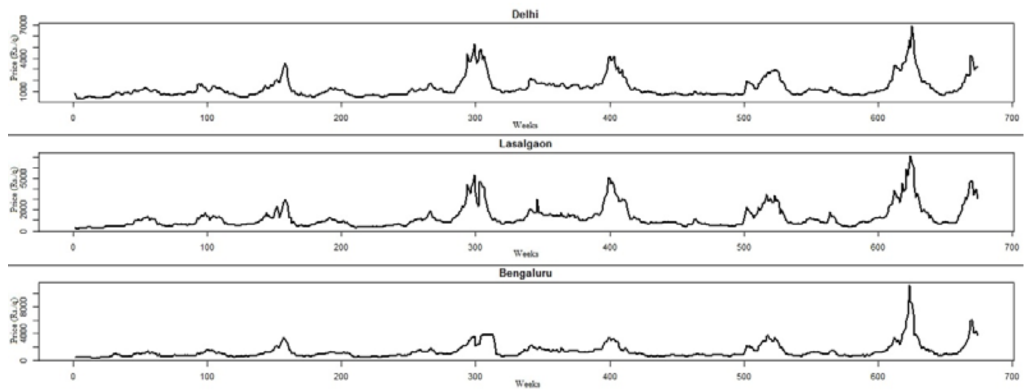

Figure 1. Time Plot of Onion Price Series for Delhi, Lasalgaon, and Bengaluru Markets.

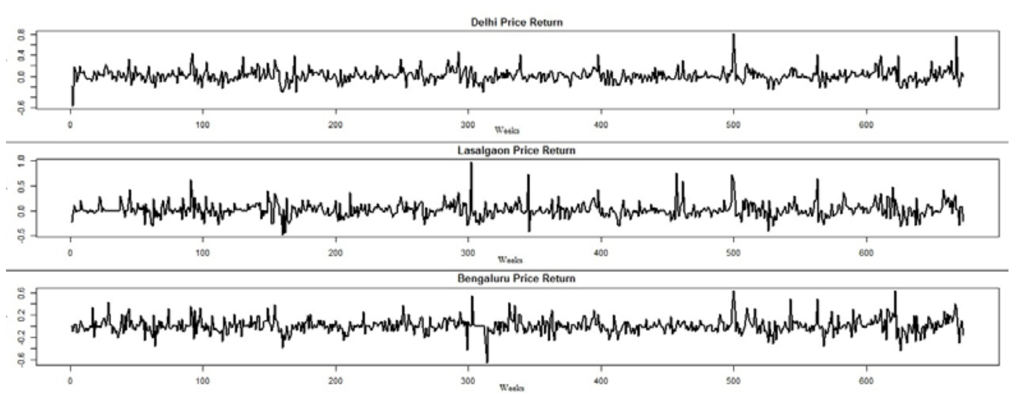

Figure 2. Plot of Price Return Series of Onion for Delhi, Lasalgaon, and Bengaluru Markets.

For any ARCH process, the distribution of innovation is as per the distribution of the data series. The most possible distribution would be the normal distribution. The normality of both the price and price return series are tested using the Shapiro-Wilk test (Shapiro and Wilk, 1965). The null hypothesis for this test is the price and price return series are normally distributed. It is seen that both the price and price return series for all the markets do not follow normality at 1 per cent level of significance (Table 2). Kernel density plots of the price, price return, and square return series are given in Figure 3. The non-normality of the price and price return series is also supported by Figure 3. The presence of excess kurtosis can also be visualised from the kernel density of the return series. Due to the presence of excess kurtosis, it is considered that the data series are following *t*-distribution. Hence, the distribution of innovation is considered as *t*-distribution.

TABLE 2. TEST FOR NORMALITY (SHAPIRO-WILK TEST)

	Delhi		Lasalgaon		Bangalore	
	Price	Price return	Price	Price return	Price	Price return
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Test statistic	0.75	0.93	0.76	0.92	0.68	0.96
p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001

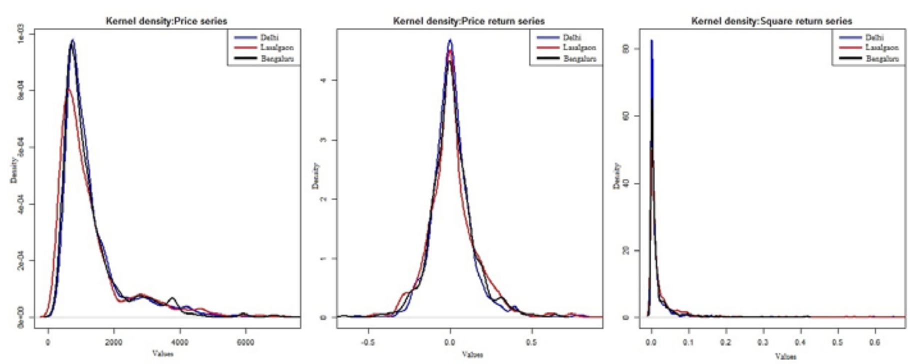

Figure 3. Kernel Density Plot for the Price, Price Return and Square Series

Before proceeding to the next step the series must be stationary. If not, then the differencing has to be done to make them stationary because ARMA methodology can only be applied for a stationary series. The stationarity of the price return series is being confirmed (Table 3) using Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979), Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Kwiatkowski *et al.*, 1992), and Phillips-Perron (PP) test (Phillips and Perron, 1988). For ADF and PP tests, the null hypothesis is that a unit root is present in the price return series. Both the tests come about as significant. But for the KPSS test, the null hypothesis is that a unit root is not present in the price return series. For this instance, the test is not significant. Hence, no further differentiation is done as all the return series are stationary.

TABLE 3. TEST FOR STATIONARITY OF THE PRICE RETURN SERIES

Test		Delhi		Lasalgaon		Bengaluru	
		Test statistic	p-value	Test statistic	p-value	Test statistic	p-value
(1)		(2)	(3)	(4)	(5)	(6)	(7)
ADF	No drift no trend	-6.74	0.01	-6.90	0.01	-6.80	0.01
	With drift no trend	-6.86	0.01	-7.13	0.01	-7.01	0.01
	With drift and trend	-6.86	0.01	-7.12	0.01	-7.01	0.01
KPSS	No drift no trend	0.64	0.10	1.27	0.09	0.89	0.10
	With drift no trend	0.03	0.10	0.03	0.10	0.04	0.10
	With drift and trend	0.03	0.10	0.03	0.10	0.03	0.10
PP		-21.19	0.01	-22.76	0.01	-23.35	0.01

The presence of statistical dependency among the observations of the price return series is inspected with the help of autocorrelation function (ACF) and partial autocorrelation function (PACF) (Figure 4). The presence of significant ACF and PACF at different lags indicate the presence of statistical dependencies among the subsequent observations. For the Delhi market, ACF and PACF are significant at lag one, three, and four. For Lasalgaon, ACF is significant at lag one and three, whereas for PACF it is lag one, three, and seven. For Bengaluru, ACF is significant at lag one to three and PACF at lag one and three. These significant spikes of the ACF and PACF also indicate the possible order of ARMA as a mean model.

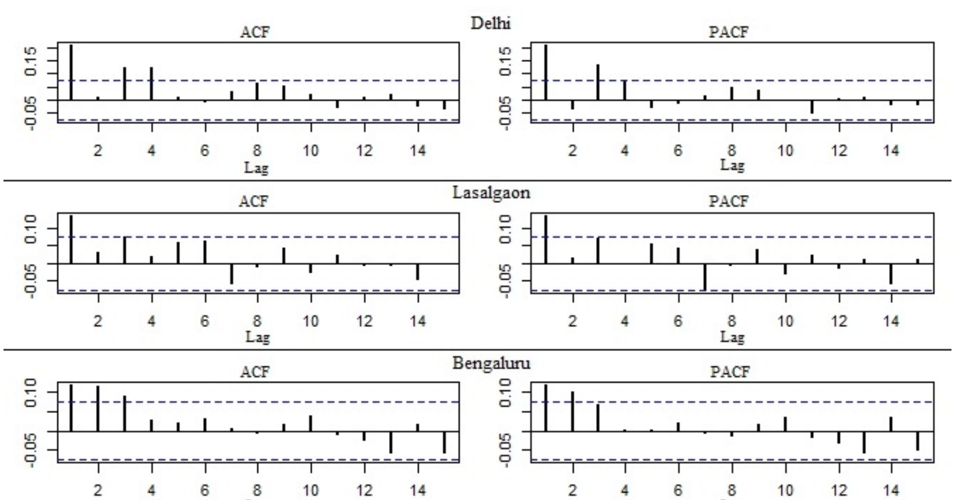

Figure 4. ACF and PACF of Price Return Series for Delhi, Lasalgaon, and Bengaluru Markets.

Different orders of ARMA are fitted as a mean model to the price return series and the residuals are obtained. The residuals are tested for the presence of heteroscedasticity by using the ARCH-LM test. The null hypothesis of this test is that there is no ARCH effect in the residual series. For all instances, the ARCH-LM tests were significant. After confirming the presence of heteroscedasticity in the residual series, asymmetric GARCH-M type of models and GARCH-M model are fitted to the residual series as variance model. The best performed ARMA order along with symmetric and asymmetric variance model is chosen (Table 4) based on minimum AIC, BIC and HQC.

TABLE 4. SELECTED ASYMMETRIC GARCH-MTYPE OF MODELS AND GARCH-M MODEL FOR DELHI, LASALGAON AND BENGALURU MARKETS

Model (1)	Delhi (2)	Lasalgaon (3)	Bengaluru (4)
GARCH-M	ARMA (0,1) -GARCH-M (1,1)	ARMA (1,0) -GARCH-M (1,1)	ARMA (1,1) -GARCH-M (1,1)
EGARCH-M	ARMA (2,2) -EGARCH-M (1,1)	ARMA (0,1) -EGARCH-M (1,1)	ARMA (1,1) -EGARCH-M (1,1)
GJR-GARCH-M	ARMA (0,1) -GJR-GARCH-M (1,1)	ARMA (0,1) -GJR-GARCH-M (1,1)	ARMA (1,1) -GJR-GARCH-M (1,1)
APARCH-M	ARMA (2,2) -APARCH-M (1,1)	ARMA (0,1) -APARCH-M (1,1)	ARMA (1,1) -APARCH-M (1,1)

The ultimate selection is done based on the extent of fitting with the actual series in terms of RSS, RMSE, MAE, and MAPE for the model building set. Moreover, for comparison of different models, the adjusted R^2 is obtained for the regression of ε_t^2 on h_t for the selected models.

For all the three markets APARCH-M model with specific ARMA order outperforms as compared to the other asymmetric variance models. The estimated parameters of the finally selected APARCH-M models are given in Table 5 for all three markets. And their extent of fitting with the original series is visualised in Figure 5 where, black dots are representing the actual values, red continuous line denote the fitted values in the model building set and blue continuous line is for

TABLE 5. ESTIMATE OF PARAMETERS OF THE BEST-FITTED MODELS FOR DELHI, LASALGAON, AND BENGALURU MARKETS

Model / Variable (1)	Delhi ARMA (2,2) -APARCH-M (1,1) (2)	Lasalgaon ARMA (0,1) -APARCH-M (1,1) (3)	Bengaluru ARMA (1,1) -APARCH-M (1,1) (4)
Mean model			
Constant	0.126 (0.010)***	0.085 (0.036)**	0.102 (0.049)**
AR (1)	0.529 (0.116)***		0.774 (0.109)***
AR (2)	0.225 (0.041)***		
MA (1)	-0.317 (0.104)***	0.149 (0.047)***	-0.704 (0.121)***
MA (2)	-0.299 (0.076)***		
λ	-1.150 (0.094)***	-0.550 (0.244)**	-0.758 (0.353)**
Variance model			
Constant	0.004(0.001)**	0.004 (0.010)	0.001 (0.000)*
a_1	0.034 (0.004)***	0.306 (0.127)**	0.012 (0.007)*
b_1	0.927 (0.001)***	0.731 (0.070)***	0.957 (0.001)***
γ	-1.000 (0.001)***	0.279 (0.132)**	-1.000 (0.002)***
δ	1.147 (0.137)***	1.826 (1.281)	1.736 (0.229)***
shape	3.767 (0.470)***	2.728 (0.358)***	3.411 (0.527)***

***p<0.01, **p<0.05, *p<0.10.

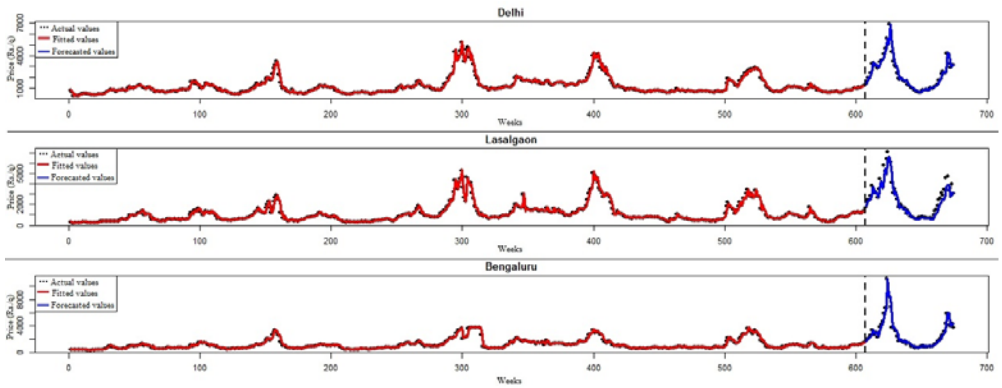

Figure 5. Plot of Actual vs. Fitted Values of The Finally Selected Models.

forecasted values in the model validation set. It seems to be very good fit for all the markets. Performance of different models evaluated in terms of RMSE, MAE, and MAPE is reported in Table 6. A perusal of Table 6 indicates that out of the three criterions, at least two criterions indicate the out-performance of APARCH model as compared to the other competing asymmetric volatility models.

TABLE 6. FITTING PERFORMANCE OF THE SELECTED GARCH-M AND ASYMMETRIC GARCH-M TYPE OF MODELS

Market (1)	Model (2)	RMSE (3)	MAE (4)	MAPE (per cent) (5)	RSS (6)	Adjusted R^2 (7)
Delhi	ARMA (0,1) -GARCH-M (1,1)	186.27	104.16	7.97	0.7475	0.0009
	ARMA (2,2) -EGARCH-M (1,1)	184.33	103.01	7.91	0.7321	0.0038
	ARMA (0,1) -GJR-GARCH-M (1,1)	185.76	104.16	7.96	0.7482	0.0004
	ARMA (2,2) -APARCH-M (1,1)	183.53	102.93	7.90	0.7327	0.0027
Lasalgaon	ARMA (1,0) -GARCH-M (1,1)	245.91	126.38	9.73	3.0078	0.0097
	ARMA (0,1) -EGARCH-M (1,1)	246.97	126.87	9.73	2.7927	0.0198
	ARMA (0,1) -GJR-GARCH-M (1,1)	245.77	126.07	9.66	2.6658	0.0150
	ARMA (0,1) -APARCH-M (1,1)	245.92	125.94	9.65	2.7647	0.0148
Bengaluru	ARMA (1,1) -GARCH-M (1,1)	194.85	106.98	9.06	1.3093	0.0367
	ARMA (1,1) -EGARCH-M (1,1)	196.06	107.12	9.09	1.1824	0.0412
	ARMA (1,1) -GJR-GARCH-M (1,1)	194.05	106.68	9.05	1.0312	0.0291
	ARMA (1,1) -APARCH-M (1,1)	194.16	106.67	9.05	0.8296	0.0006

From the parameter estimation, various inferences can be drawn regarding price volatility. For Lasalgaon $(a_1 = 0.306)$market current volatility depends more on the previous shock than Delhi $(a_1 = 0.034)$and Bengaluru $(a_1 - 0.012)$ markets. On the other hand, for Delhi $(b_1 = 0.927)$ and Bengaluru $(b_1 = 0.957)$ markets current volatility have a high degree of dependency on previous volatility but for Lasalgaon $(b_1 = 0.731)$ this dependency is slightly lesser. The asymmetric parameter γ is significant in all the cases implying the presence of asymmetry in volatility. Also, cross-correlation between the squared standardised residuals and lagged standardised residuals is computed and it is observed that for the fitted asymmetric models, the correlation is negative. For Delhi and Bengaluru asymmetric parameter γ holds its lowest value $(\gamma = -1.000)$ whereas for Lasalgaon $(\gamma = 0.279)$. It implies the presence of a high degree of asymmetry on volatility for Delhi and Bengaluru, but for Lasalgaon degree of asymmetry would be in the reverse direction with lesser intensity.

Finally, the extent of the asymmetric effect on volatility due to positive and negative shocks are visualised with the help of NICs (Figure 6). NICs of Delhi and Bengaluru markets indicate that for these markets, volatility is invariant of negative shocks and only positive shocks have a marked impact on price volatility. These graphical representations can also be explained by the estimated values of asymmetric parameter γ. For Delhi and Bengaluru $\gamma = -1.000$ and their NICs behave almost identically. The estimated numerical value indicates the highest ever possible asymmetry. For the Lasalgaon market both positive and negative shocks affect volatility but they have a different degree of impact on volatility. Here negative shocks have a more marked impact on volatility than positive shocks of equal magnitude, ceteris paribus. For Lasalgaon, the estimated value of γ is 0.279. Means asymmetry would be in the reverse direction as the sign has been changed and the degree of asymmetry would be less than Delhi and Bengaluru. The same thing is reflected through the NIC of Lasalgaon.

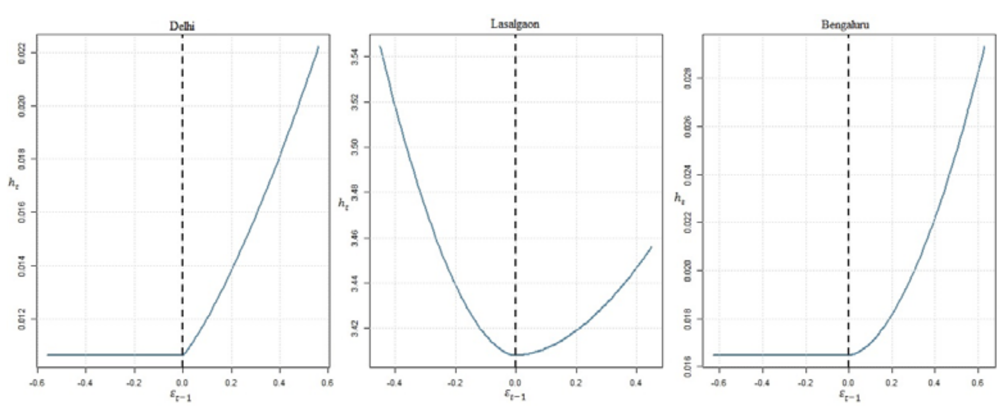

Figure 6. NICs of the Finally Selected Models for Delhi, Lasalgaon, and Bengaluru Markets.

V

CONCLUSIONS

In this study, asymmetry price volatility of onion for Delhi, Lasalgaon and Bengaluru markets are examined and its presence is confirmed. Lasalgaon market exhibits more impact on volatility due to negative shocks than positive shocks of the same magnitude. Lasalgaon is the major producers' market in India and the largest wholesale market for onion in Asia. Onion is supplied all over the country from here. Lasalgaon market is oligopolistic in nature. In case of negative shocks, the traders may try to hold back supplies to push up prices and this might induce volatility.

Another producers' market Bengaluru exhibits different behaviour of price volatility for positive and negative shocks. It can be justified that though Bengaluru is a producers' market, it is also a metropolitan city. Here onion consumption is also high. Hence, only positive shocks have a marked impact on the price volatility and it is invariant of negative shocks. Consumers' market Delhi behaves almost the same as Bengaluru. It is one of the largest consumers' markets in India. Negative shocks do not exhibit any impact but positive shocks show a high degree of impact the on price volatility.

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