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Modeling Asymmetric Volatility: A News Impact Curve Approach

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Abstract: Seasonal production, weather abnormalities, and high perishability introduce a high degree of volatility to potato prices. Price volatility is said to be asymmetric when positive and negative shocks of the same magnitude affect it in a dissimilar way. GARCH is a symmetric model, and it cannot capture asymmetric price volatility. EGARCH, APARCH, and GJR-GARCH models are popularly used to capture asymmetric price volatility. In this paper, an attempt is made to model the price volatility of the weekly wholesale modal price of potatoes for the Agra, Ahmedabad, Bengaluru, Delhi, Kolkata, and Mumbai markets using the above-mentioned models. The News Impact Curves (NICs) are derived from the fitted models, which confirmed the presence of asymmetry in the price volatility. To this end, NICs are used to describe the degree of asymmetry in volatility present in different markets.

Keywords: GARCH; News Impact Curve; volatility

MSC: 37M10

1. Introduction

The autoregressive integrated moving average (ARIMA) model is useful for capturing the linear dynamics of any time series, but it cannot address the nonlinear properties. Volatility is the unexpected variation of the realizations of a time series, and it accounts for the nonlinear component. For a financial time series, volatility may arise due to natural calamities, weather abnormalities, disruptions in the supply chain, changes in government policies, etc. Modeling asymmetric volatility is of great concern for all the stakeholders dealing with a time series. Volatility modeling can be helpful for them to make appropriate decisions at the right time and optimize resource utilization. The ARIMA model (as a mean model) along with autoregressive conditional heteroscedastic (ARCH) and its generalization, i.e., generalized ARCH (GARCH) models (as a variance model), are widely used to capture the unexpected variation of any time series.

The potato (Solanum tuberosum L.) is a crucial vegetable in Indian cuisine. Though it is not a staple food in India, in different corners of the world it is. With a growing population and increasing demand for food, it is an important crop for national food security. India ranks second in terms of potato production in the world, and it is the most produced vegetable in India. India and China together produce almost one-third of the world’s potato production. The nutritional value of a potato is also very high. It is a good source of energy, nutrients, essential amino acids, vitamins, and minerals [1,2]. Potatoes are also an important crop in terms of their food processing potential and value addition. The main segments of the potato processing industry are potato chips, French fries, potato flakes/powder, and other processed products. The potatoes should fulfill some specific
characteristics to be used for processing [3]. The potato-processing industry has a huge untapped opportunity in India.

Potatoes are grown in almost all the states of India, with a wide range of agro-climatic conditions. However, its major production is mainly confined to the North Indian states. Major potato-growing states are Uttar Pradesh, West Bengal, Bihar, Gujarat, Madhya Pradesh, and Punjab. In India, potatoes are cultivated in the winter season (rabi crop). Potatoes are generally shown during October–November and harvested during January–February. Agricultural commodity price volatility is significantly influenced by seasonality, and the month before harvest is usually the time when it is most volatile [4]. Seasonal production, along with weather abnormalities and high perishability, affects its supply chain, and potato prices exhibit a high degree of price fluctuations. Evidence [5–8] is also found in the literature that market speculation can affect the price volatility of agricultural commodities. Potatoes exhibit a relatively higher instability index (34.4%) as compared to other crops [9]. The price volatility of potatoes is of great concern for all the stakeholders, from producers to consumers, present within the supply chain. The main concern of the potato processing industry is the availability of processing varieties throughout the year at a reasonable price. Proper knowledge about price volatility behavior and its forecasting is also helpful for policymakers in their future planning, as government policies are also responsible for the volatility of commodity prices [10].

The ARIMA methodology [11] is useful to capture the linear dynamics of any time series. It cannot address the nonlinear properties of a time series, and volatility is a nonlinear attribute. The ARIMA model (as a mean model) along with Autoregressive Conditional Heteroscedastic (ARCH) and its generalization, i.e., Generalized ARCH (GARCH) models (as a variance model), are widely used to capture the abrupt fluctuation of any time series. In the Indian agricultural scenario, the GARCH model has been used in several research papers across the literature [12–15]. Statnik and Verstraete [16] showed that the price dynamics of red winter wheat, corn, and soybeans traded on the Chicago Board of Trade (CBOT) follow the GARCH model.

Though the GARCH model is very popular for addressing the volatility of any time series, it is not devoid of any limitations. The GARCH model is symmetric, it does not account for the sign of shocks and only takes into consideration the amount of shocks’ effects on volatility. Hence, it cannot capture the asymmetric behavior of price volatility, i.e., reactions to the volatility may differ depending on whether the positive and negative shocks are of the same magnitude. Many studies [17,18] highlight the asymmetric price volatility of agricultural commodities. Exponential GARCH (EGARCH), Asymmetric Power ARCH (APARCH), and GJR-GARCH models are the most frequently employed asymmetric GARCH types of models. The EGARCH model’s superiority over the GARCH in the presence of asymmetric price volatility using agricultural time series data is also established in the literature [19–21]. A study on the asymmetric price volatility of onions in India is available in the literature [22]. The present study emphasizes the presence of discrepancies in price volatility due to positive and negative shocks of the same magnitude. Asymmetric GARCH-type models such as APARCH, EGARCH, and GJR-GARCH can be used to find this discrepancy. Whether a shock is positive or negative can be determined from previous knowledge of basic assumptions. For example, flooding at the time of potato harvesting is a negative shock. In this paper, the asymmetric price volatility of six wholesale markets, namely Agra, Ahmedabad, Bengaluru, Delhi, Kolkata, and Mumbai, has been studied. Agra is the largest producers’ market in the country. Nearby districts of Ahmedabad contribute a huge amount of production, and it can also be considered a producers’ market. Kolkata is a metropolitan city, and again, its surrounding districts are major production centers. Therefore, the Kolkata market can be considered a consumers’ market as well as a producers’ market. The remaining three markets are considered consumer markets.
2. Materials and Methods

2.1. The ARCH and GARCH Models

ARIMA is a linear model that cannot address the nonlinear dynamics of a time series. Homoscedasticity in the error variance is a basic assumption of this model. By relaxing the linear and homoscedasticity assumptions, the ARCH model is introduced [23] by taking into account substantial autocorrelations present in the squared residual series to capture the nonlinear dynamics of a time series. A process \( \{ \varepsilon_t \} \) is said to follow an ARCH \((q)\) model if the conditional distribution of \( \{ \varepsilon_t \} \) given the available information \( \psi_{t-1} \) up to \( t-1 \) time epoch can be represented as:

\[
\varepsilon_t | \psi_{t-1} \sim N(0, h_t) \quad \text{and} \quad \varepsilon_t = \sqrt{h_t} \nu_t
\]

where \( \nu_t \) is known as innovation, and it is independently and identically distributed (IID) with zero mean and unit variance. The specific distribution of innovation varies with the distribution of the respective dataset. The conditional variance \( h_t \) for an ARCH \((q)\) is represented as

\[
h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j}
\]

provided to

\[
\alpha_0 > 0, \quad \alpha_i \geq 0 \quad \forall \ i \quad \text{and} \quad \sum_{i=1}^{q} \alpha_i < 1
\]

As a matter of fact, an enormous amount of parameters are required for an ARCH model to provide satisfactory precision. To overcome this problem, a more parsimonious form known as the generalized ARCH (GARCH) model was proposed by Bollerslev [24] and Taylor [25] independently of each other.

In the GARCH model, the conditional variance is also a linear function of its own lags. The conditional variance of a GARCH \((p,q)\) model is defined as

\[
h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j}
\]

The GARCH \((p,q)\) process is said to be weakly stationary if and only if

\[
\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j < 1
\]

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

\[
h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}
\]

The GARCH model only considers the dependencies of volatility on the magnitude of the shocks, and it does not consider the sign of the shocks that influence the degree of volatility. Due to this characteristic of the GARCH model, it becomes a symmetric model. Different asymmetric GARCH-type models, such as the APARCH, EGARCH, and GJR-GARCH models, have been introduced to capture the asymmetric volatility of any time series.

2.2. EGARCH Model

The EGARCH model is introduced [26] by defining the conditional variance in terms of the logarithm function. The main advantage of this model over the GARCH model, aside from addressing the asymmetric volatility, is that no restriction is imposed on the parameters as the positivity of the conditional variance is always achieved. The conditional variance for the EGARCH model is defined as

\[
\ln h_t = \alpha_0 + \sum_{j=1}^{p} \beta_j \ln h_{t-j} + \sum_{i=1}^{q} \left( \alpha_i \varepsilon_{t-i} \frac{1}{\sqrt{h_{t-i}}} + \gamma_i \frac{\varepsilon_{t-i}}{\sqrt{h_{t-i}}} \right)
\]
where $\gamma$ is the asymmetric factor that accounts for the asymmetric effect due to external shocks. For the EGARCH (1,1) model $h_t$ is reduced to

$$\ln h_t = a_0 + \beta_1 \ln h_{t-1} + \left( a_1 \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \gamma \varepsilon_{t-1} \right)$$

(7)

2.3. GJR-GARCH Model

The GJR-GARCH model [27] considers the impact of $\varepsilon_{t-1}^2$ on the conditional variance based on the sign of $\varepsilon_{t-1}$. In order to capture the sign dependence, an indicator variable is created. The $h_t$ of the GJR-GARCH model is defined as

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

(8)

where $\gamma(-1 < \gamma < 1)$ is the parameter for asymmetry and $I_{t-1}$ is the introduced indicator variable, such that

$$I_{t-1} = 1 \text{ if } \varepsilon_{t-1} < 0$$

$$0 \text{ if } \varepsilon_{t-1} \geq 0$$

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

$$h_t = a_0 + a_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \gamma \varepsilon_{t-1}^2 I_{t-1}$$

(9)

2.4. APARCH Model

In the APARCH model [28], the conditional variance $h_t$ has some asymmetric power. The $h_t$ of the APARCH model is defined as

$$h_t^\delta = a_0 + \sum_{j=1}^{p} \beta_j h_{t-j}^\delta + \sum_{i=1}^{q} a_i (|\varepsilon_{t-i}| - \gamma \varepsilon_{t-1})^\delta$$

(10)

where $\gamma(-1 < \gamma < 1)$ is the asymmetric parameter and $\delta(> 0)$ is the power term parameter. The APARCH model is a general framework of models. By assigning particular values to the parameters, the APARCH model may accommodate various orders of GARCH models. For $\delta = 2$ and $\gamma = 0$, the APARCH model is the same as the GARCH model. The $h_t$ for the APARCH (1,1) model is reduced to

$$h_t^\delta = a_0 + \beta_1 h_{t-1}^\delta + a_1 (|\varepsilon_{t-1}| - \gamma \varepsilon_{t-1})^\delta$$

(11)

2.5. ARCH-in-Mean

For the ARCH-in-mean or ARCH-M model [29], the conditional variance is also considered a predictor in the mean model. In-mean specification of models helps to capture the phenomenon that a higher perceived risk asset would typically yield a larger return. For any time series $\{y_t\}$ with its ARCH-in-mean or ARCH-M specification, the mean model can be expressed in the following form:

$$y_t = \mu + \lambda h_t + \varepsilon_t$$

(12)

where $\varepsilon_t$ is defined as an ARCH process. Higher perceived variability of $\varepsilon_t$ has an impact on the level of $y_t$, which is explained by the volatility compensation parameter $\lambda$ and $\mu$ is the mean return. $\varepsilon_t$ can also be defined as a GARCH or any asymmetric GARCH-type process. Here, the previously mentioned asymmetric GARCH-type models are used with their in-mean specifications. The application of the GARCH-M model can be found in [30].

2.6. The News Impact Curve (NIC)

Price volatility can also be affected by the nature of new information introduced into the system. Du and Dong [31] studied how the volatility of price and trade volume is affected by new information in the US dairy futures markets. The News Impact Curve [32]...
is a qualitative measure of visualizing the past return shocks to current volatility. It emphasizes the inferred association between $\epsilon_{t-1}$ and $h_t$. For calculating the NIC, all the available information up to $t-1$ epochs is considered constant, and the unconditional variance at its numerical level represents all lagged conditional variances. For a symmetric situation such as the GARCH model, the NIC is symmetric with the line of symmetry $\epsilon_{t-1} = 0$. For any asymmetric model, either the curve is asymmetric or the equation of the line of symmetry is $\epsilon_{t-1} \neq 0$.

2.7. Data Description

The daily modal spot prices (Rs./q) of potatoes for these selected markets for the time span of 1 January 2011 to 30 June 2021 were obtained from the Ministry of Agriculture and Farmers’ Welfare, Government of India [33]. From the daily price data series, the weekly price series was obtained. For further calculation purposes, the price return series of the weekly series was used, as the realization of price volatility is thought to be the square of the price return. For a financial time series $\{y_t\}$, the price return $\{r_t\}$ was calculated as

$$r_t = \frac{y_t - y_{t-1}}{y_{t-1}} \quad (13)$$

The price return series dismissed the presence of seasonal effects. The whole dataset was divided into a model-building set (first 90% of observations) and a model validation set (remaining 10% of observations).

2.8. Criteria for Selecting Order of ARMA Model

While fitting the ARMA model with different orders along with the asymmetric GARCH-type models, the best-performing ARMA order for these variance models was selected using the Akaike information criterion’s (AIC) and Bayesian information criterion’s (BIC) minimum values. These two criteria are defined as

$$AIC = -2 \ln L + 2m \quad (14)$$
$$BIC = -2 \ln L + m \ln n \quad (15)$$

where $L$ is the likelihood, $m$ is the total number of estimated parameters, and $n$ is the total number of data points.

2.9. Validation of Forecasts

Based on the following formula, the prediction accuracy of various variance models was compared in terms of root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE).

$$RMSE = \left[ \frac{1}{T} \sum_{t=1}^{T} (y_t - \hat{y}_t)^2 \right]^{\frac{1}{2}} \quad (16)$$
$$MAE = \frac{1}{T} \sum_{t=1}^{T} |y_t - \hat{y}_t| \quad (17)$$
$$MAPE = \frac{1}{T} \sum_{t=1}^{T} \left| \frac{y_t - \hat{y}_t}{y_t} \right| \times 100 \quad (18)$$

where $T$ denotes the number of observations used for validation, $y_t$ is the observed value, and $\hat{y}_t$ is the corresponding predicted value.

3. Results and Discussion

3.1. Descriptive Statistics

Table 1 provides the descriptive statistics for the selected price series. Each series comprises 548 (weeks) observations. Bengaluru exhibits the highest mean as well as median...
price, followed by Mumbai, Kolkata, Delhi, Ahmedabad, and Agra. However, for minimum and maximum prices, the same trend is not observed. Except for Bengaluru and Mumbai markets, other markets have a high coefficient of variation (C.V.) percentage for their price series. The price series of all the markets is positively skewed and leptokurtic.

Table 1. Descriptive statistics of the price series for the selected markets.

<table>
<thead>
<tr>
<th>Market</th>
<th>Agra</th>
<th>Ahmedabad</th>
<th>Bengaluru</th>
<th>Delhi</th>
<th>Kolkata</th>
<th>Mumbai</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean (Rs./q)</td>
<td>886.09</td>
<td>916.22</td>
<td>1351.24</td>
<td>1022.60</td>
<td>1096.54</td>
<td>1277.03</td>
</tr>
<tr>
<td>Median (Rs./q)</td>
<td>783.57</td>
<td>816.07</td>
<td>1278.57</td>
<td>890.86</td>
<td>981.43</td>
<td>1203.57</td>
</tr>
<tr>
<td>Minimum (Rs./q)</td>
<td>305.00</td>
<td>212.14</td>
<td>475.00</td>
<td>313.14</td>
<td>290.00</td>
<td>496.43</td>
</tr>
<tr>
<td>Maximum (Rs./q)</td>
<td>2957.14</td>
<td>2857.14</td>
<td>3500.00</td>
<td>3023.43</td>
<td>3845.71</td>
<td>3300.00</td>
</tr>
<tr>
<td>S.D. (Rs./q)</td>
<td>489.88</td>
<td>487.28</td>
<td>465.85</td>
<td>540.91</td>
<td>581.27</td>
<td>474.13</td>
</tr>
<tr>
<td>C.V. (%)</td>
<td>55.29</td>
<td>53.18</td>
<td>34.48</td>
<td>52.90</td>
<td>53.01</td>
<td>37.13</td>
</tr>
<tr>
<td>Skewness</td>
<td>1.46</td>
<td>1.23</td>
<td>1.34</td>
<td>1.36</td>
<td>1.46</td>
<td>1.24</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>2.55</td>
<td>1.65</td>
<td>2.83</td>
<td>1.93</td>
<td>2.88</td>
<td>2.36</td>
</tr>
</tbody>
</table>

The time plots of the price series for all six markets are given in Figure 1. All of these marketplaces’ price series exhibit a similar pattern. The price spikes are seen almost at the same time in all the markets. The highest price increase ever is observed around the end of 2020.

![Figure 1. The pattern of prices of the studied markets.](image)

3.2. Test for Normality

Any ARCH process’s innovation distribution depends on the available data. The Shapiro–Wilk test [34] was conducted to find out whether a series was normal. The null hypothesis for this test was that the underlying series is normally distributed. At a 1% level of significance, it can be observed that all of the price and price return series were out of the normality assumption (Table 2). The kernel density plot (Figure 2) can also be used to confirm that the price series, price return series, and square price return series were not normally distributed. The data series are thought to follow the t-distribution because of the excess kurtosis present. As a result, the innovation distribution is regarded as a t-distribution.
were not normally distributed. The data series are thought to follow the t-distribution because of the excess kurtosis present. As a result, the innovation distribution is regarded as a t-distribution.

Figure 2. Cont.
3.3. Test for Stationarity

The stationarity of the underlying time series is a prior assumption for the GARCH modeling. Using the Augmented Dickey–Fuller (ADF) test [35], Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test [36], and the Phillips–Perron (PP) test [37], the stationarity of the price return series was tested (Table 3). For the ADF and PP tests, the presence of unit root in the time series was the null hypothesis. But, the absence of unit root was the null hypothesis for the KPSS test. All three tests determined the possibility of the presence of a unit root in the return series. As all the series were stationary, no further differentiation was done.

Table 3. Testing stationarity of the price return series.

<table>
<thead>
<tr>
<th>Test</th>
<th>Agra</th>
<th>Ahmedabad</th>
<th>Bengaluru</th>
<th>Delhi</th>
<th>Kolkata</th>
<th>Mumbai</th>
</tr>
</thead>
<tbody>
<tr>
<td>ADF</td>
<td>−6.66 (0.01)</td>
<td>−6.54 (0.01)</td>
<td>−8.14 (0.01)</td>
<td>−5.98 (0.01)</td>
<td>−7.07 (0.01)</td>
<td>−7.21 (0.01)</td>
</tr>
<tr>
<td>KPSS</td>
<td>0.03 (0.10)</td>
<td>0.03 (0.10)</td>
<td>0.02 (0.10)</td>
<td>0.03 (0.10)</td>
<td>0.02 (0.10)</td>
<td>0.02 (0.10)</td>
</tr>
<tr>
<td>PP</td>
<td>−16.02 (0.01)</td>
<td>−18.05 (0.01)</td>
<td>−22.80 (0.01)</td>
<td>−16.61 (0.01)</td>
<td>−14.25 (0.01)</td>
<td>−24.09 (0.01)</td>
</tr>
</tbody>
</table>

The p-values are in parenthesis.
3.4. Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF)

The ACF and PACF plots helped to examine the statistical relationships between the realizations of a time series through visualization. When they are present, significant values of autocorrelation and partial autocorrelation at different lags indicate the statistical relationships between the successive observations. It can be seen that the ACF and PACF were decaying rapidly (exponential decay).

3.5. Fitting of Models

As the price return series for all the markets was stationary, no further differentiation was needed. ARMA models with various orders were applied as mean models, and the residual series were obtained. The ARCH-LM test was used to examine the residual series for the potential existence of conditional heteroscedasticity. The null hypothesis for the ARCH-LM test was that there was no ARCH effect in the residual series. In all cases, the tests were found to be significant. GARCH-M, APARCH-M, EGARCH-M, and GJR-GARCH-M models were fitted to the residual series. The best-performing ARMA order for these variance models was chosen depending on the AIC and BIC’s minimal values.

After selecting the appropriate ARMA order for each of the symmetric and asymmetric models for all the markets, the best-fitted models were chosen based on the degree of fitting in terms of the three popularly used error functions, namely RMSE, MAE, and MAPE, in the model building set.

The estimated parameters of the best-fitted models are given in Table 4. By applying the quasi-maximum likelihood method, parameters were estimated. For the Kolkata and Mumbai markets, the best-fitted model was the GARCH-M model. For the rest of the markets, the best-fitted models were asymmetric variance models. For the Agra, Ahmedabad, and Bengaluru markets, the best-fitted model was the EGARCH-M model. For Delhi, it was the GJR-GARCH-M model. The parameters $\alpha_1$ and $\beta_1$ indicate how the current volatility depends on previous shocks and previous volatility, respectively. For the Agra, Delhi, and Mumbai markets, the dependencies of current volatility on the previous shock were insignificant. For the remaining markets, they were significant. The dependence of current volatility on previous volatility was significant for all markets. The ARCH-M parameter $\lambda$ was significant for the Bengaluru, Delhi, and Mumbai markets. The asymmetric parameter $\gamma$ was significant for all the selected asymmetric variance models. The shape parameter for t-distribution was also significant for all instances.

Table 4. Parameter estimates of the best-fitted models for the selected markets.

<table>
<thead>
<tr>
<th>Market</th>
<th>Agra</th>
<th>Ahmedabad</th>
<th>Bengaluru</th>
<th>Delhi</th>
<th>Kolkata</th>
<th>Mumbai</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>ARMA (1,1)—EGARCH-M (1,1)</td>
<td>ARMA (1,0)—EGARCH-M (1,1)</td>
<td>ARMA (0,0)—EGARCH-M (1,1)</td>
<td>ARMA (1,0)—GJR-GARCH-M (1,1)</td>
<td>ARMA (1,0)—GARCH-M (1,1)</td>
<td>ARMA (2,1)—GARCH-M (1,1)</td>
</tr>
<tr>
<td></td>
<td>Mean Model</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.010</td>
<td>0.002</td>
<td>0.001</td>
<td>0.034</td>
<td>0.012</td>
<td>0.021</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.009)</td>
<td>(0.000) *</td>
<td>(0.014) **</td>
<td>(0.011)</td>
<td>(0.008) ***</td>
</tr>
<tr>
<td>AR (1)</td>
<td>0.743</td>
<td>0.159</td>
<td>0.316</td>
<td>0.447</td>
<td>0.976</td>
<td>0.008</td>
</tr>
<tr>
<td></td>
<td>(0.044) ***</td>
<td>(0.048) ***</td>
<td>(0.055) ***</td>
<td>(0.050) ***</td>
<td>(0.002) ***</td>
<td>(0.009)</td>
</tr>
<tr>
<td>AR (2)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MA (1)</td>
<td>−0.463</td>
<td>−0.987</td>
<td>−0.463</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.064) ***</td>
<td>(0.064) ***</td>
<td>(0.064) ***</td>
<td></td>
<td></td>
<td>(0.000) ***</td>
</tr>
</tbody>
</table>
Table 4. Cont.

<table>
<thead>
<tr>
<th>Market</th>
<th>Agra</th>
<th>Ahmedabad</th>
<th>Bengaluru</th>
<th>Delhi</th>
<th>Kolkata</th>
<th>Mumbai</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\lambda$</td>
<td>−0.103</td>
<td>−0.009</td>
<td>−0.015</td>
<td>−0.386</td>
<td>−0.272</td>
<td>−0.160</td>
</tr>
<tr>
<td></td>
<td>(0.144)</td>
<td>(0.118)</td>
<td>(0.008)*</td>
<td>(0.197)**</td>
<td>(0.187)</td>
<td>(0.066)**</td>
</tr>
</tbody>
</table>

Variance Model

<table>
<thead>
<tr>
<th></th>
<th>Constant</th>
<th>$\alpha_1$</th>
<th>$\beta_1$</th>
<th>$\gamma$</th>
<th>Shape</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>−2.530</td>
<td>−0.055</td>
<td>0.501</td>
<td>0.882</td>
<td>2.950</td>
</tr>
<tr>
<td></td>
<td>(0.770)**</td>
<td>(0.097)</td>
<td>(0.152)***</td>
<td>(0.211)**</td>
<td>(0.503)***</td>
</tr>
<tr>
<td>$\alpha_1$</td>
<td>−0.009</td>
<td>−0.126</td>
<td>0.933</td>
<td>0.456</td>
<td>4.131</td>
</tr>
<tr>
<td></td>
<td>(0.118)</td>
<td>(0.058)***</td>
<td>(0.028)***</td>
<td>(0.105)***</td>
<td>(0.880)***</td>
</tr>
<tr>
<td>$\beta_1$</td>
<td>−0.015</td>
<td>−0.334</td>
<td>0.681</td>
<td>0.957</td>
<td>2.714</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.113)***</td>
<td>(0.085)***</td>
<td>(0.218)***</td>
<td>(0.380)***</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>−0.386</td>
<td>0.049</td>
<td>0.620</td>
<td>0.597</td>
<td>3.943</td>
</tr>
<tr>
<td></td>
<td>(0.197)**</td>
<td>(0.056)</td>
<td>(0.101)***</td>
<td>(0.199)***</td>
<td>(0.707)***</td>
</tr>
<tr>
<td>Shape</td>
<td>−0.272</td>
<td>0.532</td>
<td>0.467</td>
<td>0.992</td>
<td>3.196</td>
</tr>
<tr>
<td></td>
<td>(0.187)</td>
<td>(0.130)***</td>
<td>(0.120)***</td>
<td>(0.001)***</td>
<td>(0.363)***</td>
</tr>
</tbody>
</table>

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$; S.E. is in parenthesis.

Forecasting performances in terms of error functions of the primarily selected variance models are given in Table 5. Out of the three criteria, it can be seen that the best-fitted models attained the minimum values for at least two. The residual series for all the finally selected models were tested for the possible presence of autocorrelation, and all the residual series were found to be white noise series.

Table 5. Forecasting performance of the selected models.

<table>
<thead>
<tr>
<th>Market</th>
<th>Model</th>
<th>RMSE</th>
<th>MAE</th>
<th>MAPE (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agra</td>
<td>ARMA (1,1)—GARCH-M (1,1)</td>
<td>64.557</td>
<td>39.498</td>
<td>5.097</td>
</tr>
<tr>
<td></td>
<td>ARMA (1,1)—EGARCH-M (1,1)</td>
<td>64.224</td>
<td>39.421</td>
<td>5.096</td>
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<tr>
<td></td>
<td>ARMA (1,1)—GJRGARCH-M (1,1)</td>
<td>64.408</td>
<td>39.440</td>
<td>5.094</td>
</tr>
<tr>
<td></td>
<td>ARMA (1,1)—APARCH-M (1,1)</td>
<td>64.627</td>
<td>39.556</td>
<td>5.101</td>
</tr>
<tr>
<td>Ahmedabad</td>
<td>ARMA (1,0)—GARCH-M (1,1)</td>
<td>83.371</td>
<td>54.457</td>
<td>7.191</td>
</tr>
<tr>
<td></td>
<td>ARMA (1,0)—EGARCH-M (1,1)</td>
<td>82.964</td>
<td>54.130</td>
<td>7.134</td>
</tr>
<tr>
<td></td>
<td>ARMA (1,0)—GJRGARCH-M (1,1)</td>
<td>83.184</td>
<td>54.301</td>
<td>7.169</td>
</tr>
<tr>
<td></td>
<td>ARMA (1,0)—APARCH-M (1,1)</td>
<td>82.984</td>
<td>54.135</td>
<td>7.136</td>
</tr>
<tr>
<td>Bengaluru</td>
<td>ARMA (0,0)—GARCH-M (1,1)</td>
<td>129.786</td>
<td>82.658</td>
<td>6.544</td>
</tr>
<tr>
<td></td>
<td>ARMA (0,0)—EGARCH-M (1,1)</td>
<td>128.825</td>
<td>82.176</td>
<td>6.503</td>
</tr>
<tr>
<td></td>
<td>ARMA (0,0)—GJRGARCH-M (1,1)</td>
<td>128.803</td>
<td>82.351</td>
<td>6.517</td>
</tr>
<tr>
<td></td>
<td>ARMA (1,2)—APARCH-M (1,1)</td>
<td>131.525</td>
<td>83.705</td>
<td>6.564</td>
</tr>
<tr>
<td>Delhi</td>
<td>ARMA (1,0)—GARCH-M (1,1)</td>
<td>76.020</td>
<td>50.833</td>
<td>5.629</td>
</tr>
<tr>
<td></td>
<td>ARMA (1,0)—EGARCH-M (1,1)</td>
<td>75.594</td>
<td>50.635</td>
<td>5.617</td>
</tr>
<tr>
<td></td>
<td>ARMA (1,0)—GJRGARCH-M (1,1)</td>
<td>75.468</td>
<td>50.602</td>
<td>5.612</td>
</tr>
<tr>
<td></td>
<td>ARMA (1,0)—APARCH-M (1,1)</td>
<td>75.683</td>
<td>50.666</td>
<td>5.624</td>
</tr>
<tr>
<td>Kolkata</td>
<td>ARMA (1,0)—GARCH-M (1,1)</td>
<td>80.157</td>
<td>48.394</td>
<td>4.865</td>
</tr>
<tr>
<td></td>
<td>ARMA (1,0)—EGARCH-M (1,1)</td>
<td>80.968</td>
<td>48.691</td>
<td>4.899</td>
</tr>
<tr>
<td></td>
<td>ARMA (1,0)—GJRGARCH-M (1,1)</td>
<td>80.159</td>
<td>48.400</td>
<td>4.866</td>
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<td></td>
<td>ARMA (1,0)—APARCH-M (1,1)</td>
<td>82.115</td>
<td>49.317</td>
<td>4.967</td>
</tr>
<tr>
<td>Mumbai</td>
<td>ARMA (2,1)—GARCH-M (1,1)</td>
<td>92.732</td>
<td>61.649</td>
<td>5.267</td>
</tr>
<tr>
<td></td>
<td>ARMA (0,0)—EGARCH-M (1,1)</td>
<td>93.021</td>
<td>61.896</td>
<td>5.273</td>
</tr>
<tr>
<td></td>
<td>ARMA (0,0)—GJRGARCH-M (1,1)</td>
<td>93.052</td>
<td>61.896</td>
<td>5.271</td>
</tr>
<tr>
<td></td>
<td>ARMA (0,0)—APARCH-M (1,1)</td>
<td>93.185</td>
<td>61.937</td>
<td>5.277</td>
</tr>
</tbody>
</table>

The degree of asymmetry in volatility caused by positive and negative shocks of the same magnitude can be visualized through NICs (Figure 3). For the Kolkata and Mumbai
markets, the best performing model was the GARCH model. As the GARCH model was symmetric, the NICs were also symmetric, i.e., both types of shocks with identical magnitude had similar effects on price volatility. For the other markets, the selected models were asymmetric, and their NICs were also asymmetric. For all the selected asymmetric variance models, the negative shocks had different degrees of greater influence on price fluctuation than their positive counterparts of the same magnitude. For the Delhi and Bengaluru markets, the influence of negative shocks on price volatility was much more noticeable than that of positive shocks of the same magnitude, whereas in the Agra and Ahmedabad markets, despite the fact that price volatility was more affected by negative shocks than by positive ones, the degree of asymmetry was less than in the Bengaluru and Delhi markets. Agra and Ahmedabad markets are the producers’ markets. The price volatility is influenced by factors such as weather abnormalities, policy changes, market arrivals, quantity of production, etc. The degree of these types of influences is greater in a producers’ market than in consumers’ markets such as Bengaluru and Delhi. Hence, both positive and negative shocks are more prevalent in a producers’ market than in a consumers’ market. The same is visible in Figure 3. For producers’ markets such as Agra and Ahmedabad, as both positive and negative shocks were prevalent, the price volatility was asymmetric, but the degree of asymmetry was less than in the consumers’ market. For consumers’ markets such as Bengaluru and Delhi, price volatility was asymmetric, but the degree of asymmetry was much more visible because of the relatively lower prevalence of positive shocks. It is worth mentioning that, given that we considered the nominal prices of the commodities, part of the asymmetric price volatility may be the result of monetary illusion. Moreover, the phenomenon of asymmetric price volatility as described in the present article is based on the assumption of the absence of deterministic chaos.

Figure 3. Cont.
4. Conclusions

The asymmetric price volatility of potato prices for some important markets in India is studied in this article. It is seen that out of six selected markets, the price series for Agra, Ahmedabad, Bengaluru, and Delhi exhibit asymmetric price volatility. From their corresponding NICs, positive shocks of the same magnitude are believed to have less of an influence on volatility than negative shocks. The remaining two markets, namely, Kolkata and Mumbai, exhibit symmetrical price volatility. A proper understanding of price fluctuations can be helpful for producers to make the appropriate decision at the right time to minimize their financial losses. Weather derivatives [38] can be used to mitigate the jeopardy of weather uncertainties. Predicting asymmetric price volatility may be taken into consideration in future research. Again, the effect of exogenous and endogenous shocks separately on asymmetric price volatility can be in the future scope of research. Modern cold storage facilities can be installed in the vicinity of major production centers, which can be helpful for farmers to store their produce when the prices are significantly lower.


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References


8. Staugaitis, A.J.; Vaznonis, B. Short-Term Speculation Effects on Agricultural Commodity Returns and Volatility in the European Market Prior to and during the Pandemic. *Agriculture* 2022, 12, 623. [CrossRef]


32. Engle, R.F.; Ng, V.K. Measuring and testing the impact of news on volatility. *J. Financ.* 1993, 48, 1749–1778. [CrossRef]


34. Shapiro, S.S.; Wilk, M.B. An analysis of variance test for normality (complete samples). *Biometrika* 1965, 52, 591–611. [CrossRef]


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