Price forecasting of mustard using ARIMA and EGARCH models

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Abstract
Autoregressive Integrated Moving Average (ARIMA) and Exponential GARCH (EGARCH) model was studied along with their estimation procedures for modelling and forecasting of mustard price. For forecasting mustard price ARIMA (0,1,1) model is used which gives reasonable and acceptable forecasts but the study has revealed that the AR(1)-EGARCH(1,1) model outperformed the price forecasting models for mustard prices primarily due to its ability to capture asymmetric volatility pattern.

Key words: ARIMA, EGARCH, mustard, forecasting, price

Introduction
Mustard, Brassica species, is an annual, cool season crop that is native to the temperate regions of Europe and one of the first domesticated crops. Mustard/Rapeseed cultivation is done widely throughout the world (Oplinger et al, 1991).

Mustard crop accounts for nearly one third of the oil produced in India, making it the country’s key edible oilseed crop. Due to the gap between domestic availability and actual consumption of edible oils, India has to resort to import of edible oils. It is the major source of income especially even to the marginal and small farmers in rainfed areas. Since these crops are cultivated mainly in the rainfed and resource scarce regions of the country, their contribution to livelihood security of the small and marginal farmers in these regions is also very important. By increasing the domestic production substantial import substitution can be achieved. So, the crop has the importance for farmers as well as for the nation. Accurate forecasting about the prices will help the farmer to plan the area under the crop and the traders to plan their decisions.

Prices of the agricultural commodities are important both economically and politically in almost all countries. Agricultural commodity prices strongly influence not only the farmers’ income but also consumers, agri business industry and policy makers as they are quite volatile in nature. India has a long history of policies aimed at smoothing out the price volatility for the consumers and income volatility for the farmers. But now there is need to understand the complexity of commodity price dynamics that is more urgent against the backdrop of current tendencies to remove the traditional schemes to sustain in the globalized markets. To capture these unforeseen variations in the prices of the agricultural commodities accurate forecasting models are extremely important for efficient planning and monitoring. Over the period, there have been continuous refinements in price forecasting models so that more and more accurate price forecasting can be done for the benefit of farmers and other organisations. The study on finding a best suitable method out of existing advance models of price forecasting is a useful exercise for planners, agriculture departments and other stakeholders working for price forecasting.

Thus, the present study was an attempt to identify the best suited model for the price forecasting of mustard in the Tonk district of Rajasthan.
Materials and Methods

The secondary data of monthly wholesale mustard prices for Tonk mandi were collected from the AGMARKNET site. The data of the mustard prices for the period from January 2006 to February 2016 was utilized for the analysis purpose.

Auto Regressive Integrated Moving Average (ARIMA) model and Generalized Auto Regressive Conditional Heteroscedasticity (GARCH) model were used to identify the best fitted model for the mustard crop. Exponential GARCH model was also used as it is advance form of GARCH model. The details of these models are as follows:

**Auto Regressive Integrated Moving Average (ARIMA) model**

Box and Jenkins introduced this procedure in the year 1970. The set of models introduced by them are popularly known as ARIMA models. This technique is used to forecast future values of a series based on completely its own past values. ARIMA models are most popular models for forecasting a time series which can be made to be ‘stationary’ by differencing if necessary required. A random variable that is a time series is stationary if its statistical properties are all constant over time.

ARIMA methodology attempts to describe the movements in a stationary time series as a function of ‘Autoregressive and Moving Average’ parameter. These are referred to as AR parameter (Autoregressive) and MA parameters (Moving Averages).

**Autoregressive (AR) Model**

An AR model with only single parameter may be written as 

\[ Y(t) = A_{(1)} \cdot Y(t-1) + E(t) \]

Where \( Y(t) \) = time series under investigation; \( A_{(1)} \) = the autoregressive parameter of order 1; \( Y(t-1) \) = the time series lagged 1 period; \( E(t) \) = the error term of the model.

This simply means that any given value \( Y(t) \) can be explained by some function of the previous value, \( Y(t-1) \) plus some unexplainable random error \( E(t) \).

**Generalized Autoregressive Conditional Heteroscedastic (GARCH) model**

Autoregressive conditional heteroscedastic (ARCH) model, was introduced by Engle in 1982. ARCH models are quite useful in analyzing the time series data which exhibit volatility or clustering and are

**Moving Average Models**

A second type of box-Jenkins model is called a moving average model. Although these models look very similar to the AR model, the concept behind them is quite different. Moving average parameter relate what happens in period t only to the random error that occurred in past time period, i.e. \( E(t-1) \) \( E(t-2) \) etc. rather than to \( Y(t-1) \) \( Y(t-2) \) \( Y(t-3) \) as in the autoregressive approaches.

A moving average model with one MA term may be written as follows:

\[ Y(t) = B_{(1)} \cdot E(t-1) + E(t) \]

The term \( B_{(1)} \) is called an MA of order 1. The negative sign in front of the parameter is used for convention only. The above model simply says that any given value of \( Y(t) \) is directly related only to the random error in the previous period, \( E(t-1) \), and to the current error terms, \( E(t) \).

**Mixed Models (ARIMA)**

ARIMA methodology also allows model to be built that incorporate both autoregressive and moving average parameters together. These models are often referred to as “mixed model” although this makes for a more completed forecasting tool, the structure may indeed simulate the series better and produce a more accurate forecasting. Pure model imply that the structure consists only of AR or MA parameter- not both. The model developed by this approach are usually called ARIMA model because they use a combination of autoregressive (AR) integration i.e., referring to the reverse process of differencing to produce the forecasting, and moving average (MA) operation. An ARIMA model is usually stated as ARIMA (p,d,q) this represent the order of the autoregressive component (p), the number of differencing operators (d), and the highest order of the moving average terms (q).
characterized by varying variance. This model allows
the conditional variance to change over time as a
function of squared past errors leaving the
unconditional variance constant. The presence of
ARCH type effects in financial and macro-economic
time series is well established fact. The combination
of ARCH specification for conditional variance and
the Autoregressive (AR) specification for conditional
mean has many appealing features, including a better
specification of the forecast error variance.

The ARCH (q) model for series \((E_t)\) is defined by
specifying the conditional distribution of \(E_t\) given
information available up to time \(t\).

The process \((E_t)\) is ARCH (q), if the conditional
distribution of \((E_t)\) given available information \(t-1\) is

\[(E_t) \psi_{t-1} \sim N(0, h_t)\] and
\[h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i}\]

Where, \(\alpha_0 > 0, \alpha_i > 0\) for all \(i\) and \(\sum_{i=0}^{q} \alpha < 1\)

**Generalized ARCH (GARCH) Model**

In order to overcome the limitation of the ARCH
model, Bollerslev (1986) and Taylor (1986)
independently proposed the Generalized ARCH
(GARCH) model in which conditional variance is
also a linear function of its own lags. This model is
also a weighted average of past squared residuals
but it has declining weights that never go completely
to zero. It gives parsimonious models that are easy
to estimate and even in its simplest form, has proven
surprisingly successful in predicting conditional
variances. A general GARCH model has the
following functional form:

\[e_t = \varepsilon_t h_t^{1/2} / h_t\]

**Exponential GARCH (EGARCH) Model**

The exponential GARCH or EGARCH model was
first developed by Nelson (1991), and the logarithm
of conditional variance for this model is given by:

This specification makes the effect exponential
instead of quadratic and therefore, the estimates of
the conditional variance are guaranteed to be non-
negative. The EGARCH model allows for the testing
of asymmetries.

**Forecasting Accuracy Measure**

To compare the accuracy of models Mean Absolute
Percentage Error (MAPE) is used. MAPE measures the absolute error as a percentage of
actual value rather than per period. It usually results
in elimination of the problem for interpreting the
measure of accuracy relative to the magnitude of
the actual and forecast values, as MAD does.

\[MAPE = \frac{\text{Sum} \mid X_t - F_t \mid}{\text{Sum}(X_t)}\]

Where, \(X_t\) is the actual value; \(F_t\) is the forecasted
value

**Results and Discussion**

ARIMA and GARCH models are used for price
forecasting and based on the MAPE value best
model is selected.

**ARIMA Model**

*Testing the stationarity:* The first step for applying
the ARIMA model is to check whether the series is
stationary or not. By examining the visual inspection

<table>
<thead>
<tr>
<th>To Lag</th>
<th>Chi-Square</th>
<th>DF</th>
<th>Pr&gt;ChiSq</th>
<th>Autocorrelations</th>
</tr>
</thead>
<tbody>
<tr>
<td>6</td>
<td>536.23</td>
<td>6</td>
<td>&lt;.0001</td>
<td>0.962</td>
</tr>
<tr>
<td>12</td>
<td>788.85</td>
<td>12</td>
<td>&lt;.0001</td>
<td>0.653</td>
</tr>
<tr>
<td>18</td>
<td>910.01</td>
<td>18</td>
<td>&lt;.0001</td>
<td>0.454</td>
</tr>
<tr>
<td>24</td>
<td>973.50</td>
<td>24</td>
<td>&lt;.0001</td>
<td>0.296</td>
</tr>
</tbody>
</table>
of the autocorrelation function indicated that the mustard price series is non-stationary, since the ACF decays very slowly. The result for the stationarity test is given in table 1. In this case, the white noise hypothesis is rejected based on the autocorrelation function.

Table 2: Augmented Dickey-Fuller Unit Root Tests Values after single order differencing

<table>
<thead>
<tr>
<th>Lags</th>
<th>Rho</th>
<th>Pr &lt; Rho</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-136.223</td>
<td>0.0001</td>
</tr>
<tr>
<td>5</td>
<td>-53.5592</td>
<td>&lt;.0001</td>
</tr>
</tbody>
</table>

test. The p value for the test of the first twenty four autocorrelations is observed as <0.0001, which significantly rules out the assumption of stationarity of the series. Therefore, the data series is non-stationary in nature.

As the series is non-stationary, the next step is to transform it to a stationary series by first differencing. After first differencing, Augmented Dickey-Fuller procedure was used to test the null hypothesis that means data series is non-stationary in nature and the alternate hypothesis depicts the series is stationary in nature. As p-value < 0.05 that means the null hypothesis is rejected which conclude that data series is stationary. The result of Augmented Dickey Fuller Unit Root Test is shown in table 2.

Once the mustard price series has become stationary after first differencing then different models for AR and MA combination were estimated and the model with minimum AIC and SBC was selected. After comparing various ARIMA models, ARIMA (0,1,1) model was selected. The t value provides significance of the tests for the parameter estimates and indicates whether some terms in the model may be unnecessary. In this case, the value for the moving average is 3.43 which is highly significant as shown in the table 3. Then the forecasted price of the mustard using ARIMA (0,1,1) was estimated as given in the table. The Mean Absolute Percentage Error of the ARIMA (0,1,1) is 6.2.

### GARCH Model

Testing the ARCH Effects: The Q statistics test was performed for analysing the changes in variance across time using lag windows, ranges from 1 through 12 as shown in table 4. Since the p-value for the test statistics are less than 0.0001 for all lag windows, it strongly indicates heteroscedasticity. The Lagrange Multiplier (LM) test results shown below in table 4 can help in determining the order of ARCH Model appropriate for the data. The tests are significant (p<.0001) through order 12, indicates that price series are volatile and need to be modelled using ARCH or GARCH models.

The basic ARCH (q) model is a short memory

| Parameter | Estimate | Standard Error | t Value | ApproxPr > |t| | Lag |
|-----------|----------|----------------|---------|-------------|--------------------------|-----|
| MU        | 19.89894 | 17.91986       | 1.11    | 0.2690      | 0                        |
| MA1,1     | -0.30097 | 0.08763        | 3.43    | 0.0008      | 1                        |
process in which only recent $q$ squared residuals are used to estimate the changing variance. The GARCH model ($p>0$) allows long range memory processes, which use all the past squared residuals to estimate the current variance. The LM test suggests the use of GARCH model would be appropriate instead of the ARCH model.

Different ARCH and GARCH model were calculated and their parameter estimates are given in table 5. The t-values in the GARCH estimates of GARCH 1 was not available indicating that the data was not following GARCH. Similarly other combinations of AR and GARCH were also computed but the data series was not following this model. Then the next step was to test the EGARCH model.

**EGARCH Model**

The result of EGARCH model is shown table 6.

<table>
<thead>
<tr>
<th>Table 5: Parameter Estimates for AR (1) - GARCH (1,1)</th>
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</thead>
<tbody>
<tr>
<td><strong>Parameter Estimates</strong></td>
</tr>
<tr>
<td>Variable</td>
</tr>
<tr>
<td>Intercept</td>
</tr>
<tr>
<td>AR1</td>
</tr>
<tr>
<td>ARCH0</td>
</tr>
<tr>
<td>ARCH1</td>
</tr>
<tr>
<td>GARCH1</td>
</tr>
</tbody>
</table>

<table>
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<tr>
<th>Table 6: Test Results for AR (1) – EGARCH (1,1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exponential GARCH Estimates</td>
</tr>
<tr>
<td>MAE</td>
</tr>
<tr>
<td>MAPE</td>
</tr>
<tr>
<td>Observations</td>
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<tr>
<td>Total R-Square</td>
</tr>
<tr>
<td>AIC</td>
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<tr>
<td>Normality Test</td>
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<tr>
<td>Pr&gt;ChiSq</td>
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</tbody>
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<tr>
<th>Table 7: Parameter Estimates for AR (1) - EGARCH (1,1)</th>
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<tbody>
<tr>
<td><strong>Parameter Estimates</strong></td>
</tr>
<tr>
<td>Variable</td>
</tr>
<tr>
<td>Intercept</td>
</tr>
<tr>
<td>AR1</td>
</tr>
<tr>
<td>EARCH0</td>
</tr>
<tr>
<td>EGARCH1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 8: Actual and Forecasted price of mustard by AR (1) - EGARCH (1,1) model ('/quintal)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Month</strong></td>
</tr>
<tr>
<td>January 2016</td>
</tr>
<tr>
<td>February 2016</td>
</tr>
<tr>
<td>March 2016</td>
</tr>
<tr>
<td>April 2016</td>
</tr>
<tr>
<td>May 2016</td>
</tr>
</tbody>
</table>
The EGARCH estimates show that the Mean Absolute Error (MAE) is approximately 113 and Mean Absolute Percentage Error (MAPE) in the given price data series is approximately 4. The t-value in the EGARCH estimates, as shown in table 7 of EGARCH, is significant at <.0001 indicating that the EGARCH1 is the best suited model.

The forecast obtained from applying AR(1) - EGARCH (1,1) are given in the table for month of March to May 2016 in table 8. The graph shown in figure 1 depicts the actual versus the forecasted values. On the basis of comparison of MAPE of both the models, AR (1)-EGARCH (1,1) is best-fitted model.

Conclusions

The performance of ARIMA and EGARCH has been studied using monthly wholesale price of the mustard. The EGARCH model has forecasted the volatility better than the ARIMA model. EGARCH was employed in addition to ARCH and GARCH models in order to capture asymmetry pattern of the data. The EGARCH model has outperformed the various models for the present data set as far as modelling and forecasting is concerned. Hence, the empirical results have supported the theory that EGARCH model can capture asymmetric volatility and therefore is more suitable model for price forecasting of mustard prices in Tonk district of Rajasthan.

References