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Forecasting of price volatility in cumin using EGARCH model

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Abstract

Generalized Autoregressive Conditional Heteroscedastic (GARCH) model and Exponential GARCH (EGARCH) model was studied along with their estimation procedures for modelling and forecasting of cumin price from 2006 to 2015. The Q Statistics and Lagrange multiplier test was applied to detect the presence of autoregressive conditional heteroscedastic (ARCH) effect. The study has revealed that the EGARCH model outperformed the GARCH models in forecasting of cumin prices primarily due to its ability to capture asymmetric volatility pattern.

Key words : Cumin, EGARCH, forecasting, GARCH, price

Introduction

Price forecasting is an integral part of commodity trading and price analysis. Agricultural commodity production and prices are often random as they are largely influenced by eventualities and are highly unpredictable in case of natural calamities like droughts, floods, and attacks by pests and diseases. This leads to a considerable risk and uncertainty in the process of price modeling and forecasting. Before the onset of liberalization and globalization, the government was controlling food prices, thus rendering food price forecasting a low-value added activity. Presently, the food prices are determined by the domestic and international market forces. This results into increase in price variability and accords importance to reliable price forecasting techniques.

Fluctuations in the price of different commodities are a matter of concern for consumers, farmers, agri business industry and policy makers. The unforeseen variations in prices can complicate budgetary planning. Therefore, its accurate forecast is extremely important for efficient monitoring and planning.

India is the largest producer, consumer and exporter of spices and spice products, and holds a prominent position in world spice market. Because of the climate ranging from tropical to sub-tropical to temperate, almost all spices are grown in India.

Cumin (*Cuminum cyminum* L. Family *Apiaceae*) is an important seed spice of our country. It has been grown and used as a spice since ancient times. It is mostly grown in India, Iran, Uzbekistan, Tajikistan, Turkey, Morocco, Egypt, Syria, Mexico, Chile, and China. Cumin is the dried, white fruit with greyish brown colour of a small slender annual herb. Its seeds have an aromatic odour and bitter taste. It is used as a condiment, and is an ingredient in curry powders, seasonings of breads, cakes and cheese. In medicine, it is used as a stimulant, carminative, stomachic and astringent. Cumin seed oil is used in perfumery and for flavouring liqueurs and cordials.

The spices market in India is valued at ` 40,000 crore annually. During the year 2014-15, value of spices exported from India was ` 1489968 lakh out of which cumin contributed to ` 183820 lakh contributing 12.34 per cent share of value of total spices exported (Directorate of of Aracanut & Spices Development, Ministry of Agriculture, GoI)

Looking to the importance of crop for farmers as well as for the nation prior knowledge about price of cumin is important. Accurate forecasting about the prices of cumin will help the farmers to plan the area under the crop, the traders to plan their trading decisions and to make contracts in export market also.

Materials and methods

The secondary data of monthly wholesale cumin prices were collected from the AGMARKNET site. The data of the cumin prices for the period from January 2006 to April 2016 was utilized for model fitting purpose.

Various models which use time series data are available nowadays for agriculture price forecasting viz., Auto Regressive Integrated Moving Average (ARIMA), Artificial Neural Networks (ANN) and ARCH Models etc. ARCH model and its modifications are quite advance and useful in analyzing the time series data which exhibit volatility

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or clustering and are characterized by varying variance.

a) The details of various models are as follows:

ARCH Model

Autoregressive conditional heteroscedastic (ARCH) model, was introduced by Engle in 1982. 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 (ε_t) is defined by specifying the conditional distribution of ε_t given information available up to time t-1. Let ψ_{t-1} denote this information. It consist of the knowledge of all available values of the series and anything which can be computed from these values. In principle, it may include knowledge of the values of other related time series, and anything else which might be useful for forecasting and is available by time t-1.

The process (ε_t) in ARCH (q), if the conditional distribution of ε_t for given available information ψ_{t-1} is

$$(\varepsilon_t)\psi_{t-1} \sim N(O, h_t) \text{ and } h_t = a_0 + \sum_{i=0}^{q} a\,\varepsilon_{2_{t-1}}$$

Where, $a_o > 0$, $a_i > 0$ for all I and $\sum_{i=0}^{q} a < 1$

Where (ε_t) is stochastic error condition on the realized values of the set of variables ψ_{t-1} = (y_{t-1}, x_{t-1}, y_{t-2}, x_{t-2},+.......), h_t is conditional variance and N is number of variables.

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:

$$\epsilon_t = \epsilon_t h_t^{\frac{1}{2}} h_t$$

$$= a^0 + \sum_{i=0}^{q} a_i\, \varepsilon_{t-1}^2 + \sum_{j=1}^{p} b_j h_{t-1}$$

Where $\varepsilon_t \sim$ IID(0,1) which means errors are Identically and Independently distributed. The process is linear in mean but nonlinear in variance.

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:

$$\ell_n(h_t) = a_0 + \beta \ln\left[(h_t - 1)\right] + \alpha \left|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right| + \gamma \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}$$

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 volatilities in the time series.

b) *Forecasting Accuracy Measure*

Mean Absolute Percentage Error (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.

$$\text{MAPE} = \frac{\left(\text{Sum}\left|X_t - F_t\right|\right)}{\text{Sum}\left(X_t\right)}$$

Where,

X_t is the actual value

F_t is the forecasted value

Results and discussion

Testing of 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 1. 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 1 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.

Table 1. Q and LM test for ARCH Test Disturbances

Order	Q	Pr > Q	LM	Pr > LM
1	74.6337	<.0001	69.5178	<.0001
2	122.2957	<.0001	69.5316	<.0001
3	163.2204	<.0001	70.5012	<.0001
4	196.0519	<.0001	70.5433	<.0001
5	221.4133	<.0001	70.5606	<.0001
6	244.2536	<.0001	70.6746	<.0001
7	257.1758	<.0001	71.7412	<.0001
8	267.8979	<.0001	72.2341	<.0001
9	277.5391	<.0001	72.2351	<.0001
10	284.9728	<.0001	72.2494	<.0001
11	291.4604	<.0001	72.2878	<.0001
12	295.0151	<.0001	72.7185	<.0001

The basic ARCH (q) model is a short memory 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 tests suggests that the use of GARCH model would be appropriate instead of the ARCH model.

Table 2. GARCH Test Results

GARCH Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	6339	0	Infty	<.0001
AR1	1	-0.9958	0.0164	-60.66	<.0001
ARCH0	1	654682	0	Infty	<.0001
GARCH1	1	0.0833	0.1077	0.77	0.4390

The t-value in the GARCH estimates i.e., 0.4390 as shown in table 2 of GARCH 1 is insignificant indicating that the data is not following the GARCH.

So the next step was to test the EGRACH Model. The results of the EGARCH model are shown in table 3

The EGARCH estimates show that the Mean Absolute Error (MAE) is approximately 560 and Mean Absolute Percentage Error (MAPE) in the given price data series is approximately 5%. The t-value in the EGARCH estimates, as shown in table 3 of EGARCH, is significant at 0.005 indicating that the EGARCH1 is the best suited model.

The forecast obtained from applying EGARCH (1,1) are given in the observation from 125 to 127 is for May 2016 to July 2016. The graph shown in figure 1 depicts the actual versus the forecasted values. The forecasted prices show that there will be good increase in prices in May 2016 followed by slight reduction in next two months.

Table 3. EGARCH Test Results

Exponential GARCH Estimates			
MAE	558.203355	Observations	124
MAPE	5.27418459	Total R-Square	0.8571
		Normality Test	18.8386
		Pr > ChiSq	<.0001

EGARCH Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	6300	1544	4.08	<.0001
AR1	1	-0.9864	0.0140	-70.35	<.0001
EARCH0	1	7.4886	2.1218	3.53	0.0056
EARCH1	1	0.8344	0.2443	3.42	0.0006
EGARCH1	1	0.4439	0.1601	2.77	0.0054

Table 4. EGARCH (1,1) Model Forecast

(` /q)

Period	Predicted price	Residual	Actual price
March 2016	11960.46	1507.47	13467.93
April 2016	13370.23	1318.37	14688.60
May 2016	14574.26		
June 2016	14461.48		
July 2016	14350.24		

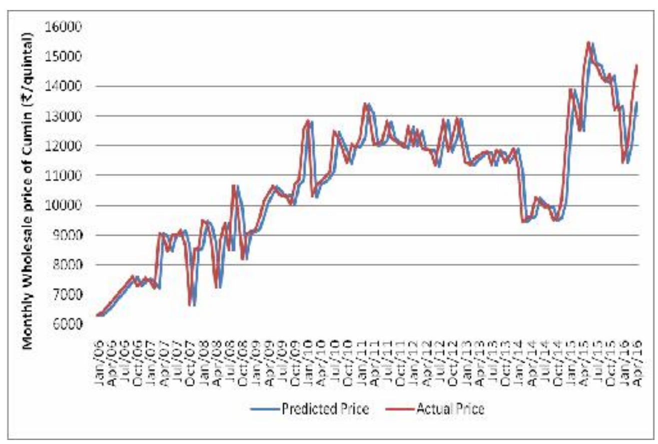

Fig. 1: Graph showing Predicted and Actual prices of Cumin using EGARCH Model

Conclusions

The performance of ARCH model and its modifications, namely GARCH and EGARCH has been studied using monthly wholesale price of the Cumin. The EGARCH model has forecasted the volatility better than the ARCH 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 GARCH 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.

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