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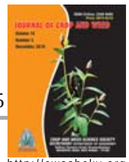

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Price dynamics of major high valued seed spices in India: an econometric insight

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ABSTRACT

Modelling and forecasting of volatility has attracted the attention of researchers for decades now. Agricultural commodity prices are characteristically fluctuating. In this paper volatile price series of spices namely Black pepper, Cardamom and Cumin are modelled and forecasted using family of Generalised Autoregressive Conditional Heteroscedastic(GARCH) model. For Cumin series due to presence of kurtosis in its residual series we have fitted GARCH model using t distributed error term. For Cardamom and Black pepper series, owing to its asymmetric nature Exponential GARCH model fitted the best. The forecasting efficiency of these models was compared with Autoregressive Integrated Moving Average (ARIMA) model using root mean squared error (RMSE) and mean absolute percentage error (MAPE). Superior results were obtained for GARCH models over the basic ARIMA model. Further, to understand the price behaviour, Coppocks Instability Index (CII) and Growth Rates (GR) for all selected spices were calculated. The study concludes by stating number of policy implications which could be advocated based on the findings.

Keywords : CII, EGARCH, GARCH, policy implications, spices, volatility

India is home to some of the most sought-after spices in the world. The history of Indian spices dates back to centuries when it had trading with the ancient civilisations of Rome and China. In present time, the Indian spices due to its rich aroma, taste and flavour are in high demand globally. The Indian domestic spices market is largest in the world which trades around 109 varieties enlisted by the International Organization for Standardization (ISO) among which about 75 varieties of spices are exported (Annual Report (2016-17), Spices Board India. The majority of the exports are made to countries like USA, China, UK and Germany. The financial year 2016-17, exhibited an increasing trend in value of the exported spices. During this period 9.5 lakh tonnes of spices and spice products valued Rs 17.6 thousand crores have been exported from the country as against 8.43 lakh tonnes valued Rs 16.23 thousand crores in 2015 witnessing a record increase of 12 per cent in volume, 9 per cent in monetary terms and 6 per cent in dollar terms of value (Annual Report (2016-17), Spices Board India. Among them three major high valued spices are Pepper, Cumin and Cardamom. These three spices contribute to about 25 per cent of the total area, around 7 per cent of the total production and most importantly contribute 22 per cent of the total export earnings (Rs. 3904.32 crore, 2016-17). The average prices of these spices (in Kg) were Rs.168.30, Rs.487.40, Rs.742.89 and Rs.1072.33 respectively for Cumin, Pepper, Cardamom (Large) and Cardamom (Small) during financial year 2017-18. High prices attract farmers for taking up such crops, but these prices have some amount of uncertainty. This can be attributed to the fact that majority of agricultural commodities prices are naturally noisy in nature and exhibits volatility. It has been observed that the response of agricultural commodity prices are quick to the real and the expected changes in demand and supply functions; and in addition to it, the climatic variations in farm production deteriorates the situation even further (Lama, *et al*., 2015).Volatility is sometimes confused with risk; the former deals with uncertainty either positive or negative, but later deals with only negative outcomes. It has been well documented in literature that the price volatility can lead to disruption of farm income and restrain the producers from investing and making optimal use of available resources (Schenepf, 1999). This leads to drawing away of much needed resources from the agricultural sector. Hence, efficient price forecasting system and better understanding of its dynamics takes centre stage for proper planning of any schemes related to particular agricultural commodities. Studies focusing on instability in area, yield and production of different crops were conducted by various researchers (Shekhawat *et al*., 2017; Reddy and Mishra, 2006; Mishra *et al*., 2013) using Cuddy-Della instability index, Coppocks Instability Index (CII) and compound annual growth rate (CAGR). These studies highlighted the importance of understanding the instability and growth pattern of a

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particular crop for making any policy recommendations. Hence, in this investigation CII and CAGR were computed for each spice considered and try to come up with few valuable insights which can lead to specific policy recommendations. For decades, volatile time-series data are being modelled and forecasted using the popular generalised autoregressive conditional heteroscedastic (GARCH) model (Li, *et al.*, 2017; Roux, 2018) introduced by Bollerslev (1986). For ease of estimation and to obtain stationary condition, GARCH model treats the parameters as linear terms and imposes the positivity constraint in the variance structure. These assumptions though helpful, it restricts GARCH model from capturing any non-linear and cyclical behaviour in the volatility process (Rabemananjara and Zakoin, 1993). Another distinguishing feature of financial series is the asymmetric volatility; volatility tends to be in higher side after a decline than after an equal rise (Nelson, 1991). Such asymmetric pattern cannot be captured using GARCH model which laid the foundation for formulation of asymmetric type GARCH models *viz.*, Exponential GARCH (EGARCH), Threshold GARCH (TGARCH) to name a few. Asymmetric extensions of GARCH model are widely used for asymmetric volatile series covering a wide domain of applications (Katsiampa, 2017; Ding, 2018). Thus, in this investigation attempt has been made to efficiently forecast and better understand the behaviour of price series for three spices (Black pepper, Cumin and Cardamom) using standard econometric tools. Few policy implications have also been discussed based on empirical findings. The paper has been divided in following sub-sections materials and method, results and discussion and finally conclusion.

MATERIALS AND METHODS

Data description

The monthly price index of Black pepper, Cardamom and Cumin were obtained from Office of the Economic Adviser, Ministry of Commerce, Government of India (www.eaindustry.nic.in) for the period April, 1994 to May, 2018). Out of 290 data points, first 284 points are used for model building purpose while the rest 6 points are used for model validation purpose. The time plot of the series (Fig. 1) is indicative of the presence of volatility at different time epochs. Looking into the descriptive statistics (Table 1) of the series one can easily point out asymmetry in the series (Skewness: 1.18, 0.82 and 0.31 respectively for Black pepper, Cardamom and Cumin).

The models explored in this study are mainly the GARCH models along with its asymmetric extensions. In this section we would introduce the models briefly. Approach followed in this investigation is two staged. In the first stage we modelled the mean using Autoregressive Integrated Moving Average (ARIMA) and then in second stage volatility was captured using GARCH models.

Estimation of growth rate

In the present study, compound growth rates of price for selected spices were estimated for the periods mentioned earlier by fitting exponential function as under

$Y_t = ab^t e_t$

Where,

Y_t is price of selected spices in time period t,

t is time element that takes the values 1, 2, 3, …n

a = Intercept or Constant

b = Regression or trend coefficient which equals to 1+ r

r = Compound growth rate

e_t = error term

On logarithmic transformation of equation

$\log Y_t = \log a + t\log(1+r) + \log e_t$

The compound growth rate was obtained as

r = [(Antilog of b) – 1] × 100

't' test was applied to test the significance of 'b' *i.e.* regression coefficient, which is-

$$t = \frac{|\hat{b}|}{S.E.(\hat{b})}$$

Estimation of instability

Extent of instability was estimated by Coppocks Instability Index (CII). CII is a close approximation of the average year-to-year percentage variation adjusted for trend (Kaur and Singhal, 1988; Reddy and Mishra, 2006).

$$CII = \left[anti\log\sqrt{logV} - 1\right] \text{x}100$$

$$\log V = \frac{\left[\log(\frac{Y_{t+1}}{Y_t}) - m\right]^2}{N-1}$$

Where,

Y_t = price in the month 't', N = Number of months

m = Arithmetic mean of the difference between the logs of Y_{t+1} and Y_t

log V = Logarithmic variance of the series.

ARIMA model

The ARIMA process can be described using the following expression :

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q} \quad (1)$$

Where, y_t and ε_t are the actual value and random error at time *t*, respectively; ϕ_i ($i = 1,2, \ldots, p$) and ($j= 1,2,\ldots, q$) are model parameters also called as the order of the model. The errors ε_t are assumed to follow an independent and identical normal distribution with zero mean and constant variance of σ^2 ($\varepsilon_t \sim$ N $(0, \sigma^2)$ $\varepsilon_t \sim iidN\,(0, \sigma^2)$)

GARCH model

The error series $\{\varepsilon_t\}$ if follows the ARCH(*q*) model is defined by specifying the conditional distribution of ε_t given the information available up to time *t "1* denoted by ψ_{t-1}. ARCH (*q*) model is denoted as

$$\varepsilon_t / \psi_{t-1} \sim N(0,h_t) \quad (2)$$

$$h_t = a_0 + \sum_{i=1}^{q} a_i \varepsilon_{t-i}^2 \quad (3)$$

where, $a_0 > 0, a_i \geq 0$ for all *i* and $\sum_{i=1}^{q} a_i < 1$ are required to be satisfied to ensure nonnegativity and finite unconditional variance of stationary $\{\varepsilon_t\}$ series. Bollerslev (1986) and Taylor (1986) independently proposed the Generalized ARCH (GARCH) model, in which they assumed the conditional variance to be a linear function of its past values and takes the following form:

$$\varepsilon_t = \xi_t h_t^{1/2}$$

$$h_t = a_0 + \sum_{i=1}^{q} a_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} b_j h_{t-j} \quad (4)$$

where $\xi_t \sim N(0, 1)$. A sufficient condition for the conditional variance to be positive is

$$a_0 > 0, a_i \geq 0, i = 1, 2, \ldots, q.b_j \geq 0, j = 1, 2, \ldots, p$$

The GARCH (*p*, *q*) process is weakly stationary if and only if

$$\sum_{i=1}^{q} a_i + \sum_{j=1}^{p} b_j < 1$$

The conditional variance defined by (3) has the property that the unconditional autocorrelation function of ε_t^2 ; if exists, has a slow decay pattern.

EGARCH model

The EGARCH model (Nelson, 1991) allows positive and negative shocks for having an asymmetric effect on the conditional variance of future observations. Another advantage being there are no restrictions on the parameters as stated by Nelson and Cao (1992). In the EGARCH model, the conditional variance, h_t, is an asymmetric function of lagged disturbances. The model is represented as

$$\ln(h_t) = a_0 + \frac{1 + b_1 B^1 + \ldots + b_{q-1} B^{q-1}}{1 - a_1 B^1 + \ldots + a_p B^p} g(\varepsilon_{t-1}) \quad (5)$$

where

$$g(\varepsilon_t) = (\theta + \gamma)\,\varepsilon_t - \gamma E(|\varepsilon_t|), \text{ if } \varepsilon_t \geq 0,$$

$$= (\theta - \gamma)\,\varepsilon_t - \gamma E(|\varepsilon_t|), \text{ if } \varepsilon_t < 0,$$

B is the backshift (or lag) operator such that

$$Bg(\varepsilon_t) = g(\varepsilon_{t-1})$$

The EGARCH model can also be presented in another way by specifying the logarithm of conditional variance as

$$1n(h_t) = a_0 + b1n(h_{t-1}) + a\left|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right| + \gamma\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \quad (6)$$

This allows the leverage effect to take an exponential form, rather than quadratic. This flexibility ensures the non-negativity of forecasts conditional variance.

RESULTS AND DISCUSSION

We have calculated the compound growth rate (GR) and instability index of these series under consideration (Table 2) using the formulae mentioned in the methodology section. We found Black pepper to have CGR and CII as 0.63 and 13.80 respectively. CGR seems healthy but instability index of 13.80 raises concern as growers will be at higher risk of price fluctuation. In case of Cardamom the CGR was highest among all at 0.67 with CII value of 10.05, farmers growing Cardamom will be at lower risk as compared to Black pepper grower, and we can expect higher returns due to high CGR. Finally, Cumin series was found to have lowest CGR and CII of 0.42 and 7.39 respectively. Hence, farmers adopting Cumin will be at least risk with respect to fluctuation in prices, but will also lower growth. It is beneficial for the farmers if growth rate in price is higher but instability is low, but generally higher growth rate leads to higher instability in prices which is not suitable for Indian. It is true for farmers throughout the world, I suppose! Farmers (more than 80% small and marginal).We also analyzed the trend of these series and obtained positively increasing trend. After having an idea regarding the growth, instability and trend of these series, we focus our attention towards capturing the price behavior of the individual series using standard models

Table 1: *Per se* performance of different spices in India during April'94 to May '2018

Series	Statistic		
	Black Pepper	Cardamom	Cumin
Mean	542.61	250.25	154.90
Standard Deviation	407.49	165.38	56.82
Kurtosis	0.05	-0.72	-0.91
Skewness	1.18	0.82	0.31
Minimum	122.70	77.20	59.70
Maximum	1517.39	663.40	285.60

Table 2 : Growth rate and instability of individual series

Sereis	Growth rate	CII
Cumin	0.42	7.39
Cardamom	0.67	10.05
Black pepper	0.63	13.8

Table 3: Test for stationarity for the series

Series		ADF test	P value	PP test	P value
Black Pepper	Level	1.54	0.77	2.41	0.95
	Differenced	4.64	<0.01	196.03	<0.01
Cardamom	Level	1.89	0.62	1.57	0.51
	Differenced	6.29	<0.01	192.33	<0.01
Cumin	Level	1.96	0.59	12.15	0.42
	Differenced	6.79	<0.01	195.72	<0.01

Table 4: Parameter estimates of ARIMA model

Series	Model parameters	
	AR	MA
Black Pepper	0.32 (0.06)	-
Cardamom	0.15 (0.05)	-
Cumin	-	-0.30 (0.06)

Note: Values in the parenthesis are corresponding standard error.

Table 5: Test for heteroscedasticity

Lags	Black Pepper		Cardamom		Cumin		Probability
	Q	LM	Q	LM	Q	LM	
1	286.49	279.20	246.26	238.01	262.76	268.52	<.001
2	564.27	279.61	444.60	238.68	494.10	268.78	<.001
3	832.50	279.62	601.61	238.72	698.59	268.83	<.001
4	1090.55	279.62	745.57	243.39	873.25	269.34	<.001
5	1339.38	279.64	884.85	243.51	1019.28	269.40	<.001
6	1577.24	279.76	1027.13	243.93	1143.97	269.61	<.001
7	1802.73	279.78	1171.79	244.41	1248.90	269.62	<.001
8	2015.64	279.80	1313.52	244.43	1335.61	269.67	<.001
9	2216.15	279.81	1441.01	244.82	1412.36	269.72	<.001
10	2404.29	279.82	1542.09	246.43	1481.23	269.75	<.001
11	2580.33	279.84	1619.46	246.53	1542.45	269.76	<.001
12	2744.76	279.88	1681.60	246.53	1599.66	269.77	<.001

Table 6: Parameter estimates of GARCH models

Series	Model	Parameters			
		a_i	b_j	Inverse of *t*	θ
Black Pepper	EGARCH(*1*,*1*)	0.29(0.06)	0.92(0.02)	-	0.55(0.07)
Cardamom	EGARCH(*1*,*1*)	0.49(0.09)	0.60(0.05)	-	0.30(0.09)
Cumin	GARCH(*1*,*1*) with *t* error	0.33(0.14)	0.54(0.15)	0.23(0.06)	-

Note: Values in the parenthesis are corresponding standard error.

Table 7: AIC and SBC values of different models

Model	Series					
	Black Pepper		Cardamom		Cumin	
	ARIMA	EGARCH	ARIMA	EGARCH	ARIMA	GARCH (*t*)
AIC	2660.22	2638.20	2636.24	2184.37	1855.94	1826.50
SBC	2667.51	2660.09	2643.54	2206.26	1863.23	1852.05

Table 8: Forecast obtained from different models

Months		Black Pepper			Cardamom			Cumin	
	Series	ARIMA	EGARCH	Series	ARIMA	EGARCH	Series	ARIMA	GARCH (*t*)
Dec-17	1281.63	1247.45	1244.94	401.97	399.85	396.62	300.36	286.21	285.62
Jan-18	1283.29	1248.59	1242.29	440.46	398.11	396.77	293.52	286.96	285.47
Feb-18	1270.01	1251.65	1241.04	450.95	396.39	397.72	285.17	287.71	285.28
Mar-18	1204.44	1255.30	1240.18	443.96	394.67	398.79	258.22	288.45	285.08
Apr-18	1161.27	1259.14	1239.43	439.76	392.96	399.89	258.86	289.20	284.87
May-18	1160.44	1263.03	1238.70	427.16	391.26	400.98	255.22	289.95	284.67

Table 9: Measures of forecasting efficiency

Forecasting Measures	Black Pepper		Cardamom		Cumin	
	ARIMA	EGARCH	ARIMA	EGARCH	ARIMA	GARCH (*t*)
RMSE	65.06	53.82	42.20	38.91	23.42	20.60
MAPE	4.72	4.12	8.73	8.04	7.48	6.61

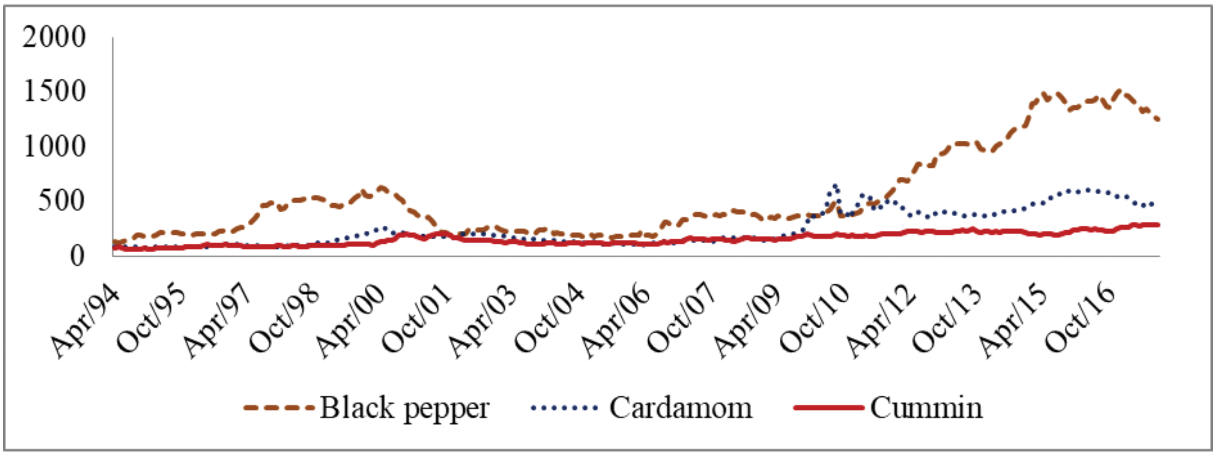

Fig. 1: Time plot of the series

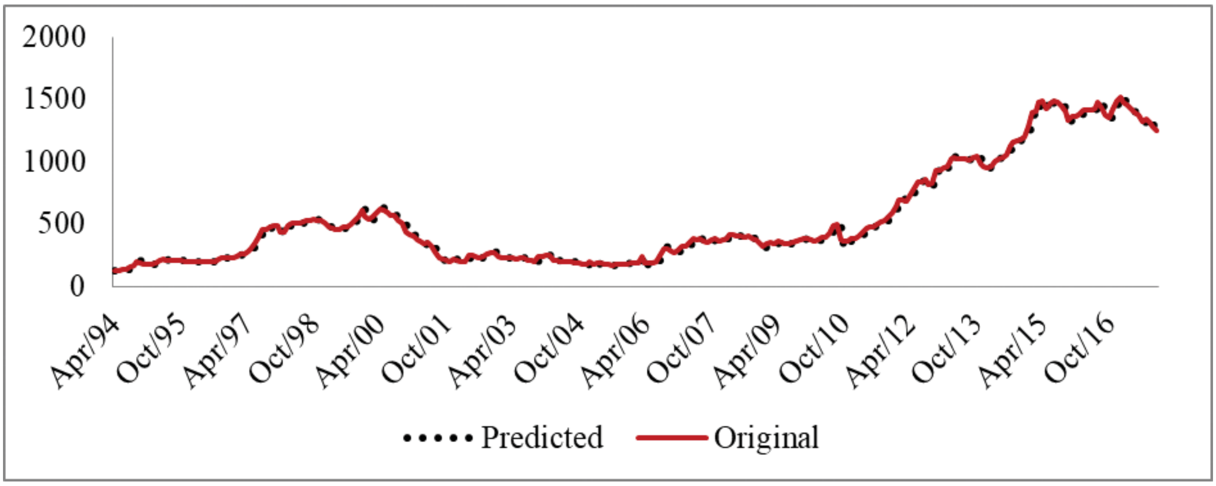

Fig. 2 a: Black pepper

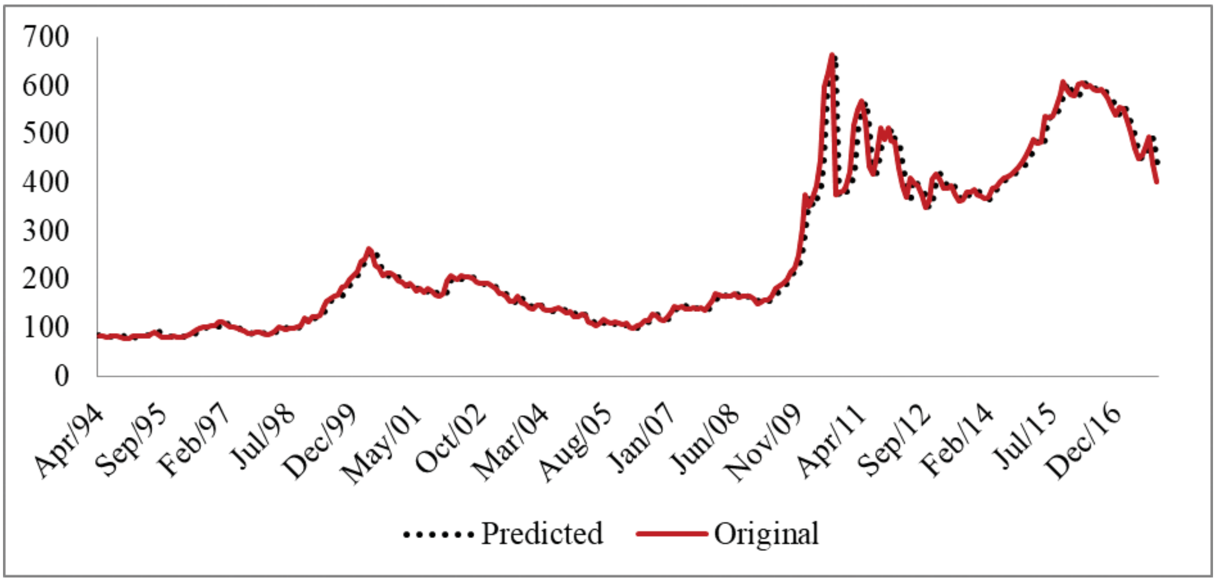

Fig. 2 b: Cardamom

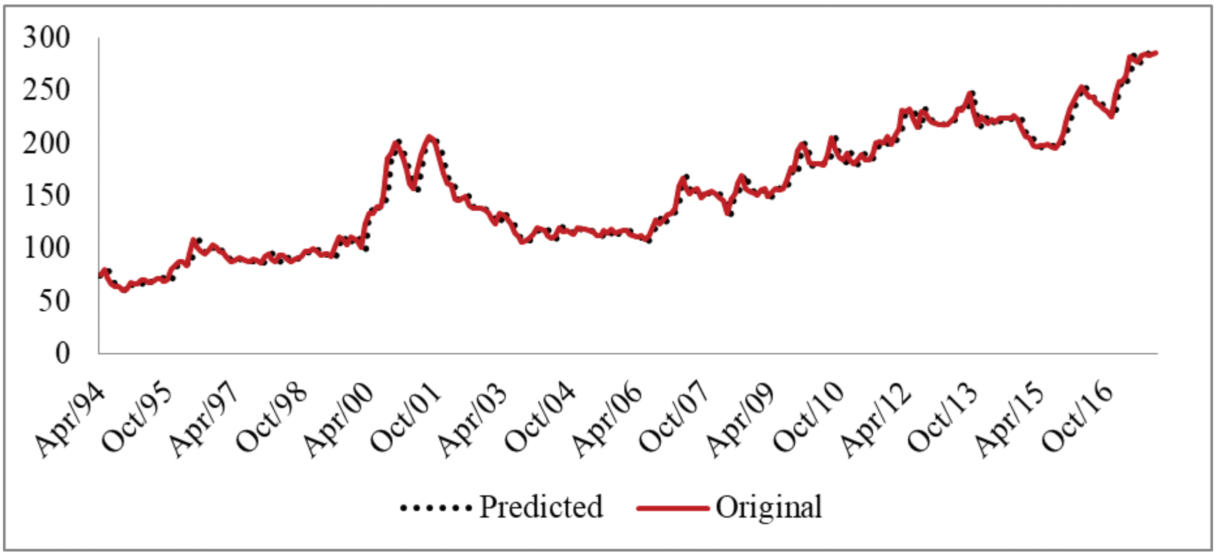

Fig. 2 c: Cumin

Fig. 2 (a,b and c): Graph of observed vs predicted for individual series obtained from the best fitted GARCH model

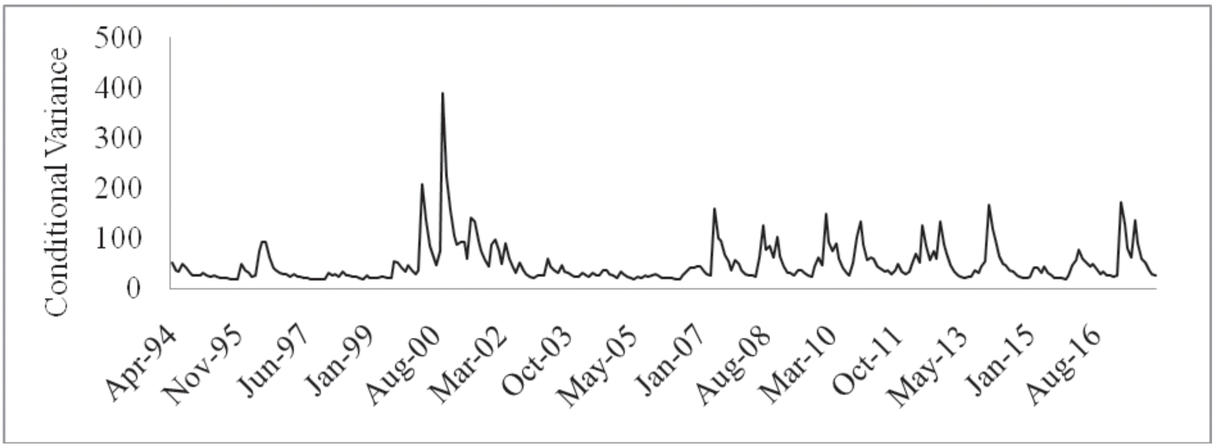

Fig. 3 a: Cumin

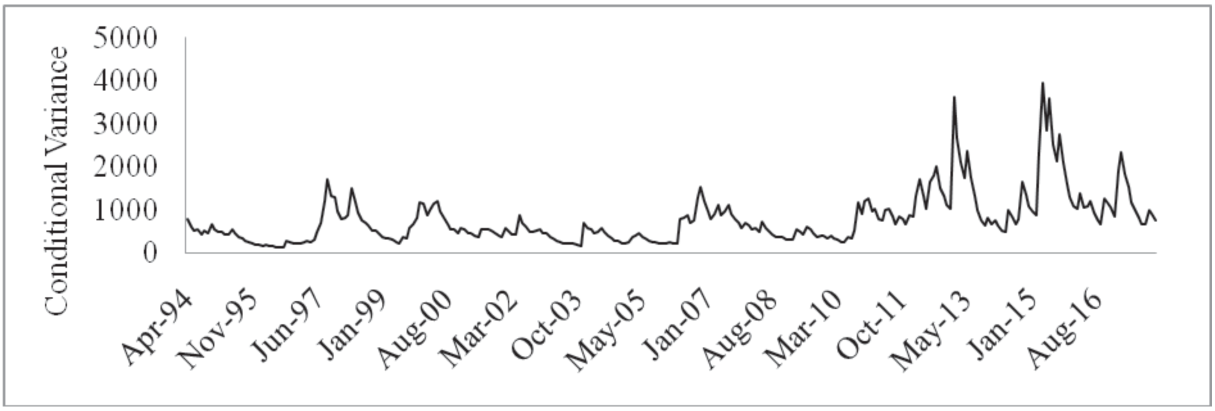

Fig. 3 b: Black pepper

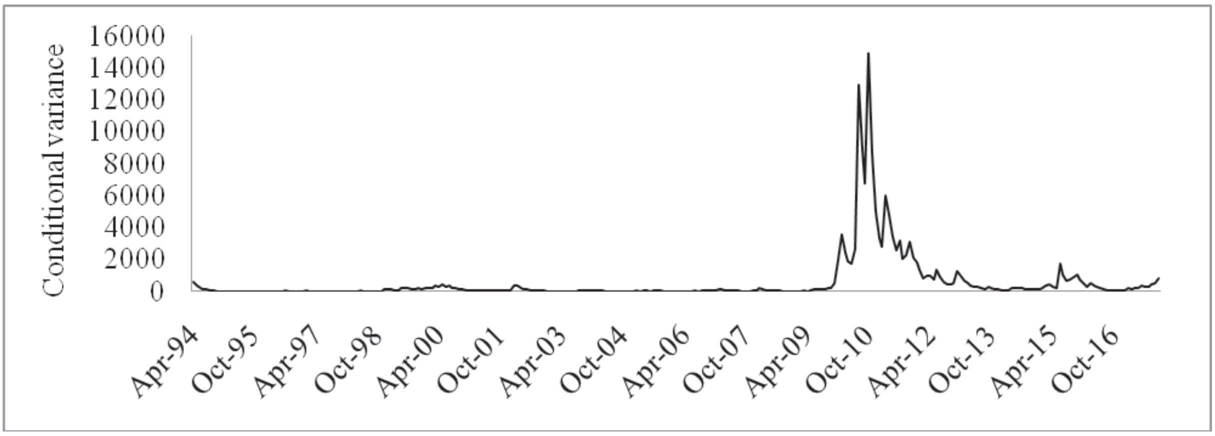

Fig. 3 c: Cardamom

Fig. 3 (a, b and c): Graphs of conditional variance for individual series

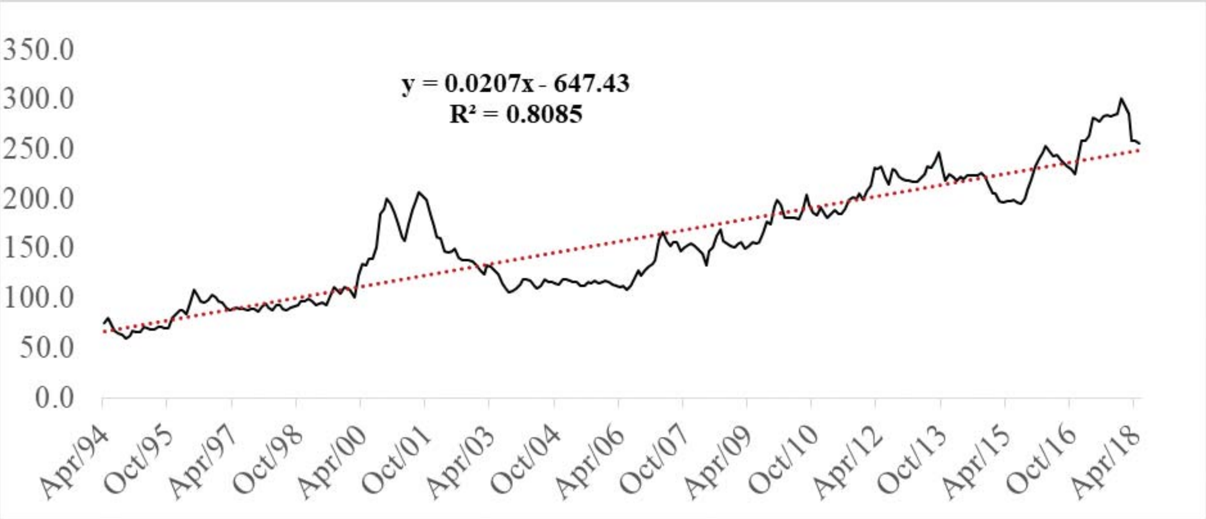

Fig. 4 a: Cumin

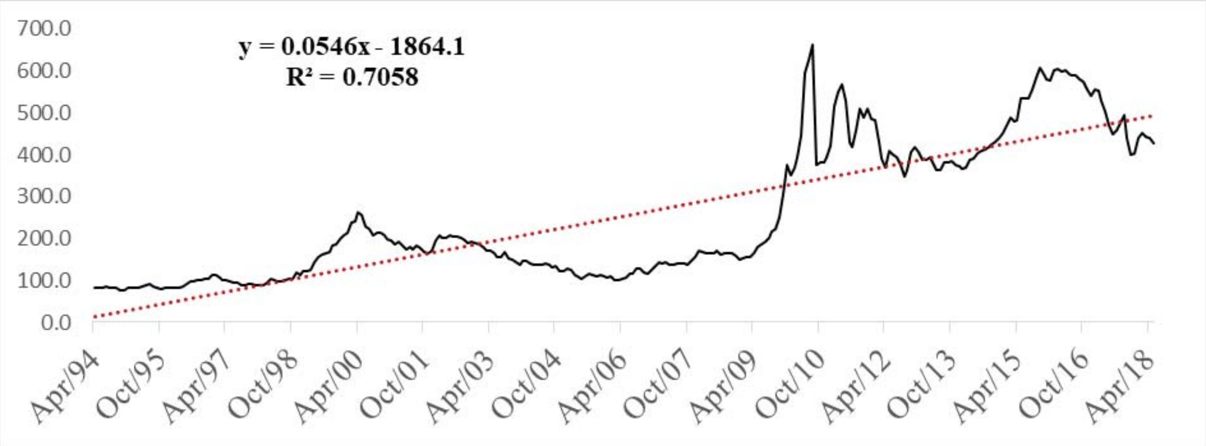

Fig. 4 b: Cardamom

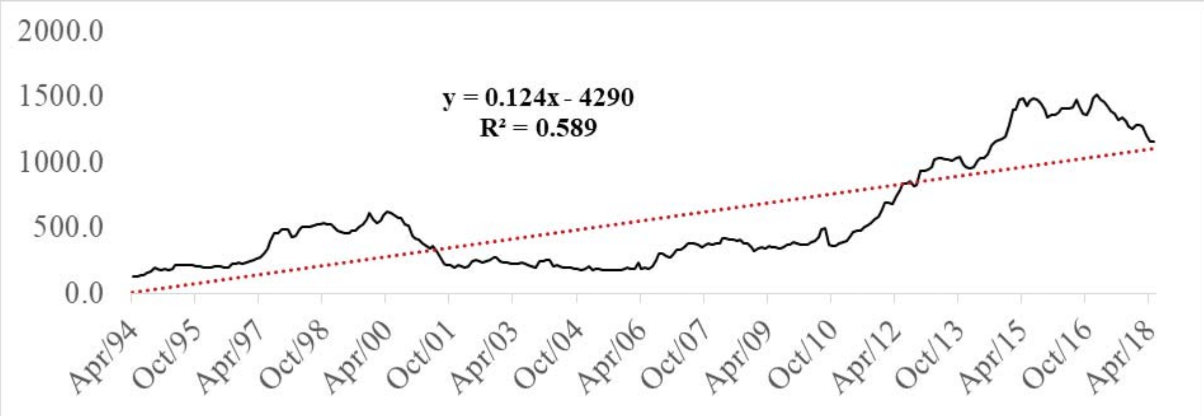

Fig. 4 c: Black pepper

Fig. 4 (a,b and c): Plot of trend equation for individual series

as described in the methodology section. We follow our pursuit using standard modelling procedure; we began with testing the stationarity (Table 3) using ADF and PP tests. As, results indicate single differencing was applied to all the 3 series considered. Next the mean effect of the series was identified using ARIMA model (Table 4). Black pepper and Cardamom series have mean dependency with their recent past value, *i.e*, AR(*1*) model whereas, for Cumin series the dependency was found to be with its recent past error term *i.e*., MA(*1*). After modeling the mean values of these series we try to explore the volatility present in them. To do so the residual analysis was carried out for testing the presence of volatility using ARCH-LM test and Q statistics (Table 5) till lag 12 why up to such lag?. Results obtained clearly indicate the presence of volatility in the series, hence providing enough evidence along with time plot to apply family of GARCH model. Various combination of GARCH models were tired but it was found that EGARCH model best suited for Black pepper and Cardamom and GARCH model with t errors for Cumin series. Table 6 reports the estimates of the model parameters along with its standard errors. For Black pepper series b_j which is indicative for the persistence of volatility was found to be 0.92 which is higher as compared to Cardamom (0.60). This implies that the impact of shock will have longer effect in the Black pepper series as compared to Cardamom series. The nature of volatility for Cardamom series is of immediate impact as compared to long run impact of Black pepper as the value of a_i is higher in Cardamom (0.49) by 1.7 times as that of Black pepper (0.29). It was also found that these two series behave differently for positive and negative shocks. The impacts of these shocks are higher in Black pepper (0.55) as compared to Cardamom (0.30). All these findings also justify the higher CII of Black pepper than the rest. The investigation found Cumin series to exhibit symmetric pattern of volatility with long run effect higher (0.54) as compared to the immediate impact of volatility (0.33). On further, analysis of the residuals from GARCH model one could find high kurtosis (2.75) which compelled to model the series with t distributed error. The selection of the models was based on lowest AIC and SBC criterion (Table 7) for modeling purpose. Fig. 2 (a,b and c) represents the graph for original vs. predicted obtained from each model for individual series, visual inspection of the graphs clearly indicates the good fit of the models. Along with it we have also checked the conditional volatility plot obtained after fitting GARCH model to each series and values of conditional variance are higher during the period where the series were volatile (Fig. 3). This phenomenon is observed when model is a good fit to the data set. To further validate the model we have forecasted for 6 months (Table 8) and compared the forecasting efficiency with ARIMA model on basis of RMSE and MAPE criterion (Table 9). For each of the 3 series prices forecasted by modelling mean and volatility together outperformed the forecasts obtained from only mean model. These findings go with literature that GARCH classes of models are efficient for capturing and forecasting volatility phenomenon (Lama *et al*., 2015) (Ref?).

This present empirical study provided few valuable insights into the three major high valued spices using its price indices. We found positively increasing trend in the prices of all the series over time. Black pepper has highest CII which make its prices very unstable, followed by Cardamom and Cumin. Another, encouraging finding from the study is that the growth rates for all three spices are positive with cardamom having highest growth. The presence of volatility both symmetric and asymmetric were identified and modelled accordingly with help of

GARCH and EGARCH model respectively. The models identified for each series performed better than the competing ARIMA model.

Based on our finding we would like to advocate the following policy implications:

1. Black pepper can be encouraged to be adopted by large scale farmers who have higher risk bearing ability and practices mix farming.
2. Cardamom should be made popular among medium and small farmers who have limited amount of risk bearing ability.
3. Cumin having lowest CII and moderate growth rate should be adopted by small and marginal farmers, who hardly have any risk bearing capabilities.

We further advocate that GOI launches certain schemes for small and marginal farmers to provide them enough financial security to bear the risk of cultivating Black pepper and Cardamom replacing Cumin. This will result to an enhanced income level of the farmers.

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