

Original Research Article

Volatility Spillover Effect of NCDEX Spot and Futures Prices in Spices

ABSTRACT

This research is an attempt to assess the volatility in spot and futures prices in spices on NCDEX. Spot price and futures price Volatility is prominent indicators of the commodity futures market to protect the interest of beneficiaries and to hedge sharp price fluctuations in commodity markets. The study tested price patterns using data with 1777 observations for FY2015 to FY2022 daily spot and futures price series of near month contracts. VECM test and EGARCH were computed to examine spot and futures prices for three selected spices, namely jeera (cumin), turmeric and coriander. The results revealed that Turmeric and Coriander had significant bidirectional relationship and Jeera had significant unidirectional relationship between futures and spot market prices. Higher half-life (days) values of futures prices indicate more stability than spot prices of selected spices. Higher asymmetric effect value of spot market indicates higher volatility impacts because of noisy shocks than futures market.

Keywords: Spot Price, Futures Price, commodity Futures Trading, Relationship, Volatility spillover, Spices.

INTRODUCTION

Indian agriculture constitutes the main occupation for around 60 per cent of the active population in rural areas (Meena, 2022). The agricultural industry is vulnerable to price risk due to a lack of product standardization, an organized market, storage facilities, proper marketing, educated knowledge about pricing in various marketplaces, and foresight about future prices of the products. The commodity futures in particular, as well as any type of financial unit are concerned about the expanding interdependence of a market with other markets. Since the value of commodities on the spot market is used to determine futures prices, markets are interdependent. As a result, the volatility in one market spreads to the other. A market's volatility of returns has a significant impact on the other market's volatility of returns if there is volatility spillover between the two markets (Edward and Rao, 2013).

“National governments have widely implemented commodities policy interventions in response to concerns about commodity price swings, including physical buffer stock systems, variable tariff schemes, stabilization funds and marketing boards” (Bose, 2008). “Due to the fact that futures prices are derived from spot market pricing for commodities, markets are interdependent. As a result, the volatility in one market "spills over" into the other market. If two markets experience volatility spillover, it means that the volatility of returns in one market has a significant impact on the volatility of returns in the other market” (Edward and Rao, 2013).

Standardized, organized and centrally located futures markets ensure that risks are shared by many investors (including speculators) in exchange for a premium and the variety of needs and viewpoints of market participants endorses effective price discovery. Producers and consumers can use futures prices as requisite indicators of expected future-ready (spot) pricing and demand-supply circumstances (Singh and Singh, 2015). In exchange for a premium, the investors are willing to assume a risk. As a result, futures contracts serve the purpose of insurance policies and the futures market operate as the meeting point for producers looking to hedge and speculators looking to insure them (Fantacciet al. 2010). Price discovery is the ongoing process of determining a price based on available information (Sendhil et al. 2013). Hedging is the process of balancing off the price risk that is present in every cash market position by assuming a position in the futures market that is equal but opposite (Bose, 2008). Excessive volatility results from investors taking short-term positions and often entering and quitting the market as more stakeholders want price risk management (Saranya, 2015).

National Commodity and Derivatives Exchange Limited (NCDEX/ the Exchange) offers three spices commodities for trading viz., Jeera (Cumin), Turmeric and Coriander. In India, cumin seed commonly known as ‘Jeera’ is the dried, white fruit with greyish brown colour of a small slender annual herb. Whereas, Turmeric is one of the most important spices as well as therapeutic agent and is grown during Kharif season and Coriander being the most widely used spices in India and around the world is one of those herbs whose all parts are edible. Keeping in view the above facts, an attempt is made to critically examine the volatility of NCDEX futures and spot prices in spices with the following specific objective is to assess volatility spillover of spices commodity market through futures and spot market prices. Among the three spices—Jeera (Cumin), Turmeric, and Coriander—Turmeric has been the most actively traded on the NCDEX

(National Commodity and Derivatives Exchange) in 2024. This is primarily due to increased domestic demand, which has driven up its trade volumes compared to Jeera and Coriander.

“Currently, NCDEX offers derivatives contracts on 11 agricultural commodities reflecting India’s identity as the world’s leading producer of agricultural commodities and the NCDEX prices are widely recognized as international benchmark prices” (Anonymous, 2022). In 2024, Turmeric saw a surge in futures trading, benefiting from improved demand in the domestic market. On the other hand, Jeera and Coriander experienced declines due to factors like subdued export demand and the arrival of new crops, which affected their prices and trade volumes. The quantities of turmeric traded was 2,03,268 MT quantity traded 4,43,634. NCDEX(2024)

REVIEW OF LITERATURE

Richter and Sorensen (2013) in their study “on stochastic volatility and seasonality in commodity futures and options of Soybeans acknowledge that soybean futures contracts displayed seasonality patterns in both spot prices level and volatility”.

Saranya (2015) reported “a similar direction for volatility spill from spot to futures for majority of the commodities studied. The causality test and generalised autoregressive conditional heteroskedasticity (GARCH) was used for analysing the futures market for a few selected commodities from 2008 to 2014. Volatility was seen to be steadily decreasing”.

Vasantha and Mallikarjunappaa (2015) examined “the lead-lag relationship of pepper in India by employing Johansen’s cointegration test, ECM-EGARCH models. Augmented Dickey-Fuller (ADF) test is used to check the stationarity of the price series and it was found that there is a long run co integration between the two markets in terms of price discovery. This result is further supported by the results of volatility spillover obtained from EGARCH model. Therefore, spot market influences in price discovery process. Since the spot market is informationally more efficient than the futures market, hedgers can take spot market prices as base”.

Manogna and Mishra (2020) found that “the results from EGARCH volatility test that there exist mutual spillover effects on futures and spot markets. Thus, it could be inferred that futures market is more efficient in price discovery of agricultural commodities in India”.

METHODOLOGY

To examine the main objectives of the study, secondary data on selected spices crops (i.e., Jeera, Turmeric, Coriander) were collected from the reports available on NCDEX website. The data set comprises of daily closing spot prices and near-month futures contract prices for each commodity. The historical price reports were collected for a period of seven years from 2015-16 to 2021-22 with 1777 observations. For the purpose of the study, selection of appropriate and sufficient data is significant to achieve the best possible outcomes. In this context, sampling is taken from the available data at NCDEX platform. For measures of central tendency, dispersion, skewness and kurtosis, a total of seven years data is taken. Since Covid 19 pandemic has highly impacted all sectors including agriculture. Post covid 19, commodity futures market dominates the prevailing market through digital platform wherein the buyers and sellers are able to fulfill their demand and supply efficiently. Because of this reason, the study data from FY 2019-20 to 2021-22 is considered as a **sample**.

For assessing the volatility spillover, the data is taken from FY 2019-20 to FY 2021-22 excluding the dates that have insufficient data (whether of futures price or spot price or both) in order to fulfil the demand of model applied for continuous data. VECM (Vector Error Correction Model) is used to analyze whether a set of variables are found to have one or more cointegrating vectors mentioned in equation 1. This is a suitable estimation technique which adjusts to both short-run changes in variables and deviations from equilibrium. To assess volatility spill over EGARCH model is applied rather than ARCH and GARCH models because these models impose the non-negative constraints on the parameters, α_i and γ_j , while there are no restrictions on these parameters in the EGARCH model. **Consequently, the EGARCH model was selected for this analysis because it does not impose non-negative constraints on the parameters, α_i and γ_j , unlike the ARCH and GARCH models.**

Analytical tools and statistical techniques

Vector error correction model (VECM)

After confirming that the two series are cointegrated with a common stochastic trend, we proceed to represent the spot and future prices using the VECM as per the cost-of-carry relationship to examine the lead-lag dynamics. Hasbrouck(1995) describes this common stochastic trend as the common implicit efficient price in the cointegrating system. The bivariate

cointegrated series, $P_t = (Y_t, X_t)$, is represented by a VECM:

$$\Delta X_t = C_X + \lambda_1 Z_{t-1} + \sum_{i=1}^k \alpha_{X,i} \Delta X_{t-1} + \sum_{i=1}^k \beta_{X,i} \Delta Y_{t-1} + \varepsilon_{X,t} \quad \text{-----(1)}$$

$$\Delta Y_t = C_Y + \lambda_2 Z_{t-1} + \sum_{i=1}^k \alpha_{Y,i} \Delta Y_{t-1} + \sum_{i=1}^k \beta_{Y,i} \Delta X_{t-1} + \varepsilon_{Y,t} \quad \text{-----(2)}$$

$$Z_{t-1} = X_{t-1} - b_i Y_{t-1} \quad \text{-----(3)}$$

Where, a is the speed of adjustment coefficient or error correction term (ECT) that measures the convergence speed to long-term equilibrium state and β constitute the short-run adjustment coefficient. Z_{t-1} is the error correction term that amounts to the unbalanced error of the bivariate time series and long-run multiplier represented by b_i . α , The alpha coefficients represent the speed of adjustment toward the long-run equilibrium relationship captured by the error correction term Z_{t-1} in equation 3. They indicate how quickly X_t and Y_t adjust in response to deviations from the long-term equilibrium in equation 1 and equation 2. k denotes the number of lags included in the model. The summation notation indicates that the equation includes k lagged values of the differenced variables ΔX_t and ΔY_t . the adjustment coefficient measures the causal relationship between the future and spot prices and denotes the rate at which short-term adjustments gradually correct the long-term equilibrium relationship between spot and future prices. Thus, the VECM allows us to analyze both the long-term equilibrium relationships and the short-term dynamics within the system, providing a comprehensive understanding of the interplay between these two processes. The optimal lag length for VECM is identified using vector autoregressive (VAR) model, a simple extension of autoregressive (AR) framework and the lags are chosen based on AIC (Akaike information criterion) criteria, The AIC is often preferred because it strikes a balance between model complexity and goodness-of-fit, focusing on predictive accuracy. It is particularly useful in smaller samples and dynamic models like VECM, where capturing both short-term and long-term dynamics is crucial. This choice may also reflect familiarity within the field. ECT coefficients are used to compute half-lives of the shocks from the

equilibrium position. Half-life of shocks in both the spot and futures markets is calculated using the formula 4:

$$\text{half-life of shocks} = \frac{\ln(0.5)}{\ln(1 - |\text{ECT coefficient}|)} \text{-----}(4)$$

Exponential generalized autoregressive conditional heteroskedasticity (EGARCH)

This study focuses on how news from one market affects the volatility of the other market. A simple GARCH model generally suggests a negative conditional variation and is not suitable for further inferences. To overcome the negative problem to take logs on both sides of the GARCH equation, we consider the EGARCH model, which explains volatility more accurately than GARCH model. Thus, the conditional variance for the EGARCH (p, q) is used to examine the volatility spillover between futures price and spot price in Indian agricultural commodity market.

$$\ln(h_t) = \varphi + \sum_{i=1}^q \eta_i \left| \frac{\varepsilon_{t-i}}{\sqrt{h_{t-i}}} \right| + \sum_{i=1}^q \lambda_i \frac{\varepsilon_{t-i}}{\sqrt{h_{t-i}}} + \sum_{k=1}^p \theta_k \ln(\varepsilon_{t-k}) \text{-----}(5)$$

LHS is the log of variance series (h_t) which automatically restricts the volatility to a positive value, makes the leverage effect exponential rather than quadratic. This ensures that the estimates are non-negative. The equation 5, constant level of volatility, which is a function of volatility, is represented by coefficient φ , η is the ARCH effects, λ is the asymmetric effects and θ is the GARCH effects. If $\lambda_1 = \lambda_2 = \dots = 0$ the model is symmetric. If $\lambda_i < 0$ it implies that bad news (negative shocks) generates larger volatility than good news (positive shocks). But if $\lambda_i > 0$ it implies that good news (positive shocks) generates larger volatility than bad news (negative shocks). The uncorrelated residuals $\varepsilon_{s,t-1}$ and $\varepsilon_{F,t-1}$ in the given equations are obtained from VECM (Equations (1) and (2)) are used in the bivariate EGARCH (1,1). This approach is equivalent to a

joint estimation of the VECM and EGARCH models as estimating them simultaneously is not practical for large number of parameters. constant (φ_i) implies for level of volatility of any time series data. The ARCH effect is concerned with a relationship within the heteroskedasticity and is used to estimate risk due to volatility in any time series data. GARCH effect describes financial markets in which volatility can change, becoming more volatile during periods of financial crises or world events and less volatile during periods of relative calm and steady economic growth.

Ordinary Least Squares (OLS) Regression Analysis

The existence of volatility, downside potential, and volatility spillover give a clear signal about the risk in the market segment. To mitigate the price risk, we need to estimate the constant hedge ratio. It is important to determine how many contracts have to be purchased to minimize the risk exposure. The conventional approach of OLS regression in a linear regression of the change in spot on the change in futures prices is depicted by the following equation:

$$R_s = \alpha_0 + \alpha_1 R_f + \varepsilon_t \quad (6)$$

R_s and R_f are the return value of spot price and futures price, respectively; α_1 is the slope coefficient of OLS regression, which is the estimate of the optimal hedge ratio h^* (also known as the MV hedge ratio) (Myers and Thompson, 1989).

Now,

$$h^* = \partial \frac{\sigma_s}{\sigma_f} \quad (7)$$

Where σ_s is the standard deviation of spot prices, and σ_f is the standard deviation of futures prices. The OLS estimation is simple, dynamic, and robust in nature. We have to look for valid and efficient results while dealing with OLS. The error term in the equation will be heteroscedastic in case any violation occurs in the assumptions. On first assumption, the spot and futures price must have a pure random walk. Secondly, ε_s and ε_f should be normally distributed. The OLS regression uses unconditional sample moments rather than conditional moments (Park and Switzer, 1995). The basis must decline in the futures contract and reach zero in the convergence month; this is clearly observed in the direct hedge environment (Fama, 1965).

RESULTS AND DISCUSSION

The daily return price series for the three commodities are examined using the EGARCH model to explore the volatility spillover between the spot and futures markets. To evaluate the model's suitability, diagnostic tests of serial correlation and goodness-of-fit metrics have been carried out. The issue of unit roots was addressed by testing the series for stationarity using methods like ADF or PP tests. If non-stationary, the data was differenced to achieve stationarity, enabling dynamic analysis through VECM, which examines both short-term dynamics and long-term equilibrium relationships in cointegrated series. The joint estimation of the VECM and EGARCH models is identical to the empirical analysis in the bivariate EGARCH model, which uses the VECM residuals.

Vector Error Correction Model (VECM) Outcomes

To check the short-run and long-run relationship between the spot (S) and futures (F) price series, VECM has been performed. Error correction terms (ECT) coefficients (i.e., α_S and α_F) have been reported in Table 1 instead of complete VECM with lags. It is seen the number of observations for jeera, turmeric and coriander is 598, 547 and 621 respectively. In the case of Spot Price Return, the Error correction terms (α_S) for jeera is -0.12, for turmeric it is -0.15 and for coriander it is -0.08. Likewise, in the case of Futures Price return, the Error correction terms (α_F) for jeera is -0.04, for turmeric -0.02 and for coriander it is -0.07. All these values are statistically significant at 5 per cent except, for the error correction terms for Futures Price return of jeera which is not significant.

Table 1: VECM statistics for selected Spices

Commodity	Observations	Adjustment coefficients/E CT		Correlation	Half-life(days)	
		Spot market (α_S)	Futures market (α_F)		Spot	Futures
Jeera	598	-0.12*	-0.04	0.98	5.52	18.91
Turmeric	547	-0.15*	-0.02*	0.97	4.36	28.53

Coriander	621	-0.08*	-0.07*	0.98	8.89	9.14
Note(s): * indicate significance 5 per cent level of confidence. SD stands for standard deviation. Half-life is shown in days for our daily data.						

Source: Authors' compilation based on model results

The adjustment coefficients indicated that there was a unidirectional causal relationship between the spot and futures markets for jeera and coriander, and a bidirectional causal relationship between the spot and futures markets for turmeric and coriander, both at a 5 per cent level of significance. All of the examined commodities have absolute values of α_S greater than α_F , which suggests that spot prices would react to any disequilibrium between future and spot prices more quickly than future prices. It shows that the futures market, as opposed to the spot market, is more effective in reflecting new information to prices. We therefore conclude that the futures market is crucial to the process of determining prices for all three commodities.

Half-life of the shocks from the equilibrium position is calculated using ECT coefficients. According to Table 1, the ECT coefficient for jeera's future market is -0.04, which suggests that the half-life of noisy shocks in the futures market is 18.91 days, whereas the half-life in the spot market is 5.52 days. The half-life of loud shocks for turmeric is 4.36 days for the spot market as well as 28.53 days for the futures market. For coriander, the half-life of noisy shocks in the futures market is 9.14 days as opposed to 8.89 days in the spot market. When the market's ECT coefficient decreases, the half-life of noisy shocks increases. The higher the half-life value, the greater the market's contribution to price discovery, which suggests that for jeera, turmeric, and coriander, price discovery is dominated by the futures market. This should be viewed as an addition to our earlier findings regarding the importance of ECT coefficients and Granger causality studies.

EGARCH Model Outcomes

In the bivariate EGARCH (1,1) results shown in Table 2, it is noted that the number of observations each for jeera, turmeric and coriander is 555. All values of the given parameters are significant at 1 per cent level of significance. Hence, the null hypothesis (H_0) is rejected which means that the values of all parameter are volatile. The value of constant (ϕ_i) for spot prices series for jeera, turmeric and coriander is 4.52, 29.16 and 7.87 respectively. However, the value of constant (ϕ_i) for futures prices series for jeera, turmeric and coriander is 3.13, 5.09 and 3.60

respectively. The higher values of constant for spot price series revealed higher volatility in spot market as compared to futures market in all the selected commodities.

Table 2: EGARCH statistics for selected Spices

Sl. No.	Commodity	Prices	Observations	Parameter			
				Constant (φ_i)	ARCH effect (η_i)	Asymmetric effect (λ_i)	GARCH effect (θ_i)
1	Jeera	Spot	555	4.52**	6.75**	7.20**	87.56**
		Futures	555	3.13**	3.87**	4.99**	77.52**
2	Turmeric	Spot	555	29.16**	22.05**	16.49**	4.86**
		Futures	555	5.09**	8.85**	16.04**	77.51**
3	Coriander	Spot	555	7.87**	5.88**	8.38**	41.12**
		Futures	555	3.60**	2.81**	6.48**	46.75**

Note: ** indicates significant at 1 per cent level of significance.

Source: Authors' compilation based on model results

The value of ARCH effect (η_i) for spot price series for jeera, turmeric and coriander is 6.75, 22.05 and 5.88 respectively. The value of ARCH effect (η_i) for futures prices series for jeera, turmeric and coriander is 3.87, 8.85 and 2.81 respectively. The higher values of ARCH effect for spot price series revealed higher risk in spot market as compared to futures market in all the selected commodities. The value of GARCH effect (θ_i) for spot prices series for jeera, turmeric and coriander is 87.56, 4.86 and 41.12 respectively. Also, the value of GARCH effect (θ_i) for futures prices series for jeera, turmeric and coriander is 77.52, 77.51 and 46.75 respectively. The significant values of GARCH effect (θ_i) for spot and futures price series revealed that price becomes more volatile during periods of financial crises or world events and less volatile during periods of relative calm and steady economic growth.

The value of Asymmetric effect (λ_i) for spot prices series for jeera, turmeric and coriander is 7.20, 16.49 and 8.38 respectively. Likewise, the value of Asymmetric effect (λ_i) for futures prices series for jeera, turmeric and coriander is 4.99, 16.04 and 6.48 respectively. The positive values of the asymmetric effect (λ_i) suggest that positive shocks (good news) lead to higher volatility, which is typically linked to increased risk. Speculators can cushion this risk by employing hedging strategies such as using futures contracts to lock in prices, thereby mitigating the adverse effects of potential market downturns. Additionally, options strategies like buying call options provide upside potential with limited downside risk. The response rate to "good news" often depends on market conditions, liquidity, and the underlying asset's sensitivity, leading to potentially faster adjustments in prices and opportunities for speculators to capitalize on these movements.

On the other hand, the positive coefficient of volatility spillover (asymmetric effect) means that the future (spot) market is slow to adjust to spot (future) market to restore an equilibrium point. These results also revealed that as the information flow increases in the futures market, the volatility of spot market also increases.

The adjustment coefficients showed a bidirectional causality between spot and future market in turmeric and coriander and unidirectional causality between spot and future market in jeera. Error correction terms are higher than absolute terms for all of the commodities chosen, which suggests that spot prices would react to any disequilibrium between future and spot prices more quickly than future prices. It shows that, in comparison to the spot market, the futures market is more effective at reflecting new information to prices. **The sustainability of these short-term half-lives hinges on market liquidity and transaction costs, impacting profitability. Speculators might leverage high-frequency trading or automation to exploit these opportunities while carefully managing logistics and costs. These results are partially comparable to other agricultural markets but underscore the need for tailored strategies due to differing market dynamics and commodity-specific factors.** With a decrease in the market's ECT coefficient, loud shocks have a longer half-life. The higher the half-life value, the greater the market's contribution to price discovery, which suggests that for jeera, turmeric, and coriander, price discovery is dominated by the futures market. The results for Turmeric and Coriander are on par with Manogna and Mishra (2020).

In the bivariate EGARCH (1,1) results indicated the futures (spot) market takes a while to react to the spot (future) market in order to return to equilibrium due to the positive coefficient of

volatility spillover (asymmetric impact). These results also revealed that as the information flow increases in the futures market, the volatility of spot market also increases. The results are contradicting with Manogna and Mishra (2020).

CONCLUSION

The positive coefficient of volatility spillover means that the future (spot) market is slow to adjust to spot (future) market to restore an equilibrium point. The positive coefficient of volatility spillover suggests slow market adjustment, implying policymakers may need to enhance market efficiency and integration. For traders, this lag creates arbitrage opportunities but also demands careful risk management to capitalize on market disparities without incurring significant losses due to delayed equilibrium restoration. These results also revealed that good news (positive shocks) generates larger volatility than bad news (negative shocks) for spot and futures market in all the selected commodities. Speculators should come in investment action at the time of good news, means speculators should consider entering the market when positive shocks occur, as these moments bring potential profit opportunities due to increased volatility. However, since larger volatility also implies greater risk and the effects are short-lived, speculators need to act swiftly and manage risks carefully.

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REFERENCES

1. Anonymous, 2022, NCDEX overview. Available at: <https://www.ncdex.com> (Retrieved on 29 September 2022)
2. Bose, S., 2008, Commodity futures market in India: A study of trends in the national multi-commodity indices. *Money Finance ICRA Bull.*, **3**(3): 125–158.
3. Edward, A.J. and Rao, N.T.V., 2013, Price discovery process and volatility spillover of chilli spot and futures prices: evidence from National Commodity and Derivative Exchange Ltd (NCDEX). *Int. J. Exclusive Manag. Res.*, **3**(12): 1–23.
4. Fama, E. F., 1965, The behaviour of stock market prices. *J. Business.* **38**(1): 34–105.
5. Fama, E. F., 1970, Reply to efficient capital market: a review of theory and empirical work. *J. Finance.* **25**(1): 383-417.
6. Fantacci, L., Marcuzzo, M. C. And Sanfilippo, E., 2010, Speculation in commodities: Keynes' practical acquaintance with futures markets. *J. Hist. Econ. Thought.* **32**(3): 397–418.
7. Hasbrouck, J., 1995, One security, many markets: determining the contributions to price discovery. *J. Finance.* **50**(4): 1175-1199.
8. Manogna, R. L. and Mishra, A. K., 2020, Price discovery and volatility spill over: empirical evidence from spot and futures agricultural commodity markets in India. *J Agribus. Developing Emerging Economies.* **10**(4): 447-473.
9. Myers, R. J. and Thompson, S. R., 1989, Generalized optimal hedge ratio estimation. *Am. J. Agric. Econ.*, **71**(4): 858–868.
10. Park, T. H. and Switzer, L. N., 1995, Time varying distributions and the optimal hedge ratios for stock index futures. *Appl. Financial Econ.*, **5**(1): 131–137.

11. Richter, M. and Sorensen, C., 2013, Stochastic volatility and seasonality in commodity futures and options: the case of Soybeans. Available at: <https://ssrn.com/abstract=301994> (Retrieved on 30 September 2022).
12. Saranya, V. P., 2015, Volatility and price discovery process of Indian spot and futures market for non-agricultural commodities. *Int. J. Manag. Social Sci.*, **3**(3): 346–354.
13. Sendhil, R., Kar, A., Mathur, V.C. and Jha, G. K., 2013, Price discovery, transmission and volatility: evidence from agricultural commodity futures. *Agric. Econ. Res. Rev.*, **26**(1): 41–54.
14. Singh, A. and Singh, N. P., 2015, Testing seasonality and efficiency in chana futures market. *Apeejay Business Rev.*, **14**(2): 5–15.
15. Vasantha, G. And Mallikarjunappa, T, 2015, Lead-lag relationship and price discovery in Indian commodity derivatives and spot market: an example of pepper. *IUP J. Appl. Finance.* **21**(1): 71-83.