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Do volume and open interest explain volatility?: An inquiry into the Indian commodity markets
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Abstract

Purpose – The purpose of the paper is to study the explainability of expected and unexpected trade volume and open interest as information flow, and the asymmetric effects of unexpected shocks to the information flow on volatility in Indian commodity markets.

Design/methodology/approach – After having dissected into expected and unexpected components, the effects of trade volume and open interest on volatility are tested. A new interaction term is also added to measure asymmetry. Four commodities, namely, cumin, soy oil and pepper in food commodity category and guar seed in non-food commodity category are selected for the present study. These four commodities are selected based on their economic and trading importance, i.e. weight in the index and trading volume (liquidity).

Findings – It is mostly found that unexpected volatility is positively related to the volatility, and the effect of the unexpected component is more than the expected component of the trading volume. The expected open interest is negatively related to volatility while the unexpected open interest is found to be positively related in all the commodities. The effects of unexpected component are higher than the expected open interest. The effects of positive unexpected shocks to the trade volume are more than those of negative unexpected shocks. The evidence of asymmetry in unexpected shocks to open interest is inconclusive. However, the inclusion of volume of trade and open interest could not vanish away the volatility. This indicates that the trading volume and open interest are not the variable with mixed distribution. Thus, it contrasts the assumption of mixed distribution hypothesis, and they do not proxy the flow of information.

Practical implications – It is the unexpected information flow that matters more than the expected one. Positive unexpected shocks to trade volume are more influential than the negative shocks. However, trade volume and open interest are not good proxy of information flow in the Indian commodity markets. This study would definitely broaden the horizon of managers and policymakers to understand the volatility better.

Originality/value – The paper is unique in terms of understanding the effect of expected and unexpected trade volume and open interest and the asymmetric effects of unexpected shocks to volume and open interest in the Indian commodity markets.

Keywords Volatility, India, Trade volume, Open interest, Asymmetry, Commodity markets

Paper type Research paper

JEL classification – G10, G11, C32

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1. Introduction

The old saying about the relationship between price volatility and flow of information in the Wall Street that "It takes volume to make prices move" has gained increased attention over a period of time. However, this causality can be questioned not only in the equity markets but also in the commodity markets. It is widely believed that trading volume and open interests are the proxy of flow of information, which drive the price changes. There are different opinions on the relationship between trading volumes and price volatility. One school of thought believes that the difference in investors' opinion and expectations causes changes in trading volumes and volatility and describes the dynamics of these two terms (Admati and Pfleiderer, 1988; Harris and Raviv, 1993; Wang, 1994; He and Wang, 1995). The second school of thought, on the contrary, opines that new information arriving at the markets influences trading volume and volatility (Clark, 1973; Copeland, 1976; Jennings *et al.*, 1981). He and Wang (1995) argued that equilibrium prices are believed to reflect investors' private information on the basis of which they trade. However, at times, the plan does not work because of the noise[1] present in the process. Copeland (1976) and Simirlock and Starks (1988) stated that new information arrives at the market in a sequential manner under *Sequential Information Arrival Hypothesis*. Information reaches one trader at a time, and trading, thus, occurs in a sequence only after every trader receives information. This suggests that trading volume and price changes occur sequentially. On the other hand, Clark (1973) and Tauchen and Pitts (1983) mostly talked about information as merely a mixing variable under *Mixture of Distribution Hypothesis* (MDH). Under this hypothesis, the price and trading volume change synchronously in response to the arrival of new information where trading volume acts as a latent mixing variable, i.e. returns are a result of mixture of distributions and trading volume is a mixing variable. Harris and Raviv (1993) and Shalen (1993) put forward *The Dispersion of Beliefs Approach* where they established that greater the dispersion of beliefs among traders, the higher the volatility/volume relative to their equilibrium values. Unlike other hypotheses, it is the dispersion of expectations which measures the excess volume of trade and excess price volatility. This phenomenon is associated with market noisiness in the speculative markets, and this may be the reason that the major changes in price are unaccompanied by equal major news or liquidity (volume of trade) shocks. This is due to the fact that traders hold different opinions about the information flow. This particular approach accounts for both informed and uninformed traders. Uninformed traders respond to changes in volume/price as if these changes reflect new information. Conversely, informed traders, based on homogenous beliefs, trade on the prices of fair value, and therefore, uninformed traders shake prices to increase volatility. Another explanation of *The Information Trading Volume*, given by Blume *et al.* (1994), argues that volume plays an informationally important role in an environment where pricing signals are of different quality.

Trading volume contains information regarding the quality of pricing received by traders leading to form a link among trading volume, quality of information flow and volatility. Karpoff (1987) cited 18 different studies to confirm the positive relationship between volatility and volume and put forward four reasons behind the importance of this relationship. First, it gives a lens to understand the structure of the financial markets. Second, it helps in event studies that use a combination of price and volume data to infer. Third, it is important to the discourse over the empirical distribution of speculative prices. Finally, it also plays a significant role in understanding the futures markets in terms of speculation and stabilizing or destabilizing effects. It is considered that high trade volume leads to high liquidity of the market, resulting into the movement of prices in line with the trade volume. This may attract more hedgers, as they participate in the futures markets to stabilize their future cash flows, while speculators participate on the basis of their expectations about futures price movement or volatility. Open interest is used as a proxy to market depth, so it is believed that when market depth increases, volatility declines. Thus, it seems that volatility is not the only important aspect but it is also important to understand how it exists in relationship to volume and open interest.

In this backdrop, this study has attempted to examine the issue of volatility, trade volume and open interest by raising four questions:

(1) Are trade volumes and open interests good proxy for the daily information flow to explain volatility?

(2) Are trade volumes and open interests positively and negatively related with volatility, respectively?

(3) It is deemed that market reacts more to the unpredictable or private information flow than the expected information. Therefore, is volatility caused more due to unexpected information flow, i.e. unexpected trade volume and open interest?

(4) This study also makes further attempt to understand the relationship between shocks to volume and open interest, and volatility. Positive unexpected volume and open interest shocks have larger impact than negative shocks. Thus, do positive unpredicted shocks to the volumes and open interests have more impact than negative shocks?

Evidence mostly shows that unexpected trading volume and volatility are positively co-related, and the effects of unexpected components are higher than the expected components. While the expected open interest is negatively co-related with volatility, the unexpected open interest is found to have a positive relationship with volatility. Inclusion of both expected and unexpected components of trading volume and open interest cannot eat away the whole Generalized Autoregressive Conditional Heteroscedasticity (GARCH) effects.

The paper is divided in four sections. Section 2 presents a brief literature review. Section 3 narrates the methodology adopted in this study. Section 4 reports the results and discussion, and section 5 presents the conclusion.

2. A brief literature review

The study of the relationship between information flow and volatility has always been an area of research. Some of the recent studies include those of Foster (1995), Fujihara and Mougoue (1997) and Girma and Mougoue (2002) who found a positive relationship between trading volume and volatility in light crude oil, heating oil and unleaded gasoline for the period from 1984 to 1993. Foster (1995), favouring the MDH, found that even after inclusion of volume, persistence in volatility still exists, and thus, he concluded that there are some other factors which affect volatility persistence. Besides, he also found a bidirectional non-linear causality between returns and volume and stated that this feedback predictability may exist even between volume and volatility.

Girma and Mougoue (2002), favouring *Sequential Information Arrival*, found that volume and open interest separately explain volatility and obtain reduction in volatility persistence when lagged weighted average open interest and volume are used together to explain future volatility. Karpoff (1987) stated that new information has a negative effect on the investor's demand. At times, the variance of inter-temporal change in transaction supply is lower in comparison to transaction demand in response to the information arrival, as short-selling is not desirable due to the cost attached to it. This leads to positive covariance between volume and price. Lamoureux and Lastrapes (1990) used contemporaneous or lagged trading volume as an explanatory variable in the variance equation and found that the inclusion of volume eliminates the persistence in the volatility. But on the flip side, Chen *et al.* (2001) reported that persistence in volatility is not eliminated when lagged or contemporaneous trading volume level is incorporated into the GARCH model. Najand and Yung (1991) performed similar analysis, but with Treasury bond futures, and reported that lagged volume explains volatility better than contemporaneous trading volume. Arago and Nieto (2005) re-examined the results of Lamoureux and Lastrapes (1990) and argued that it would be better to split trading volume into two parts – one is normal, expected by the market, and the other is influenced by the unpredictable flow of information to the market, which is an unexpected volume. They discovered that the unpredictable component of trading volume has a larger impact but has no significant effect on the persistence of volatility.

In some research, market depth has also been included to explore the relationship among volatility, trading volume and market depth. Kyle (1985) defined market depth as the order flow required to move prices by one unit which was also used by many other researchers (Bessembinder and Seguin, 1992, 1993; Fung and Patterson, 1999). Bessembinder and Seguin (1992) argued that depth varies with recent trading activity, which is proxied by endogenously determined open interest. When open interest is large, it is expected that observed volatility, condition upon contemporaneous volume, would be lower. Hence, market depth provides additional information on return volatility. A positive relationship between volatility and volume and a negative relationship between open interest and volatility were concluded by them. Bessembinder and Seguin (1993) represented some methodological improvement and included both lagged signed forecast errors and lagged daily standard deviations and allowed the relationship between unexpected return and volatility to vary, depending on the sign of the unexpected return. Their study was carried out on data of developed nations. They concluded that unexpected volume and open interest not only have a larger impact but also positive unexpected shocks to volume, and open interest have more impacts than negative shocks. Recently, Mahmood and Salleh (2010) examined the dynamic relationship between price volatility, trading volume and market depth in Malaysian Futures Market and found that there is a positive effect of expected and unexpected volumes, and market depth on volatility. Javadi (2012) examined that trade volume does not extract all the information of volatility, although the unexpected component of trade volume has been found to be positively related with conditional volatility. He conducted his study on S&P 500 index of US equity markets by using GARCH (1,1) and Glosten, Jagannathan, and Runkle [GJR(1,1)] models.

In emerging markets, Kuo *et al.* (2005) studied the relationship among price volatility, trading activity and market depth for some selected contracts in Taiwan and Singapore derivatives markets using ordinary least squares-based and GARCH models and found that high volatility is characterized with high trading volume, thereby supporting MDH argument.

In the Indian context, Pati (2008) estimated GARCH and GARCH–GJR models with expected and unexpected components of volume and open interest and found positive relationship between trading volume and volatility, and negative relationship between expected open interest and volatility. Kumar and Pandey (2010) observed that there is positive relationship between trade volume and volatility, whereas the relationship between open interest and volatility is found to be insignificant. However, volatility is more explained by its own lags rather than information flow. Market trading activity is not a good proxy for information flow.

The study of the relationship between information flow and volatility is mostly restricted to security and energy futures. This is also true in the Indian context. Commodity futures have received relatively scant attention given the size of the market. The asymmetric effect of shocks to unexpected information flow is another aspect which needs to be explored for better understanding of the relationship between volatility and information flow.

3. Data and methodology

3.1 Data and sample

Four agro commodities – pepper, cumin and soy oil in food commodity category and guar seed in non-food commodity category – were selected for the present study. These four commodities were selected based on their economic and trading importance which are weight on the whole index and trading volume (liquidity). Cumin is considered to be one of the highest exported spices contributing up to 10 per cent of the value of total spice export. India is the largest exporter, producer and consumer of cumin. It is a well-known fact that pepper and cumin are the highest and second highest traded and liquid spices commodities, respectively, with INR79,518.79 trillion and INR55,982.69 trillion volume of trade, respectively in 2011-2012, respectively (Forward Markets Commission, March, 2012 Report). In National Commodity and Derivatives Exchange (NCDEX) platform, Dhanya, the commodity futures index, gives a weight of 17.42 to the spice group (chilli, cumin, pepper and turmeric), in which pepper and cumin have 3.11 and 4.33 weightage, respectively. Systematic risk of pepper and cumin is 0.68 and 1.51, respectively (NCDEX Institute of Commodities Market and Research Report, 2011). Refined soy oil is the highest traded agro commodity. The value of futures trading of soy oil is INR538383.46 trillion, implying 35.44 per cent of total value of major food items and 24.51 per cent of total value agro commodities (Market Review of April 2012, Forward Markets Commission Monthly). High volatility due to international price movement is the characteristics of soy oil. Guar seed trading, in the category of non-food commodity, is the highest in 2011-2012. During 2011-2012, the volume and value of trading of guar seed stood at 73.31 million tonnes with a total value of INR338216.190 trillion (Forward Markets Commission, 2012 Report). Guar seed also enjoys the status of being the second highest traded agro commodity after refined soy oil.

Data were collected from the NCDEX due to it being the leading commodity exchange in agricultural commodities and the National Multi Commodity Exchange. Daily close prices cover the period from the point of inception of trading of each commodity to December 2011. The data of cumin, pepper and guar seed range from March 2005 to December 2011 (total number of observations of 1917), from August 2004 to December

2011 (total number of observations of 2,170) and from July 2004 to December 2011 (total number of observations of 2,240), respectively. The sample period of soy oil is taken from December 2008 to December 2011. Data of soy oil futures before December 2008 could not be used, as there was a ban on soy oil futures trading, which could mislead the analysis.

3.2. Methodology
3.2.1 Modelling conditional volatility
3.2.1.1 GARCH model. GARCH (p, q) models are a plausible method to model volatility by avoiding the limitation of a long-lag structure. The GARCH (p, q) process along with seasonality and structural breaks is as follows:

$$\sigma^2 t = \alpha_0 + \sum_{i=1}^{q} \alpha\ i\ \varepsilon^2{}_t - i + \sum_{j=1}^{p} \beta j h_{t-j}$$
$$= \alpha_0 + \mathrm{A}(L)\varepsilon^2{}_t + \mathrm{B}(L)h_t \qquad (1)$$

where, p $\geq$ 0, q > 0, $\alpha_0 > 0$, $\alpha_i \geq 0$, i $\geq$ 1….q, β_i=0, j=1….p.

For p = 0, the process reduces to the (autoregressive conditional heteroscedasticity (ARCH) (q) process, and for p = q = 0, ε_t is simply a white noise. $\varepsilon^2{}_{t-i}$ are the past observations (ARCH term), and h_{t-j} are the past conditional variances (GARCH term). α_0, α_i and β_j in the equation (1) are the constant, ARCH and GARCH coefficients, respectively.

In the ARCH (q) process, the conditional variance is specified as a function of past sample variances only, whereas the GARCH (p, q) process allows lagged conditional variances to enter as well. This corresponds to some sort of "adaptive learning mechanism".

3.2.1.2 GARCH–GJR model. GARCH–GJR was first introduced by Glosten *et al.* (1993). In this model, good and bad news have differential impacts on conditional variance. Good news has the influence of α, while bad news has the impact of ($\alpha + \gamma$). If $\gamma > 0$, it could be inferred that there is a "leverage effect", while news is asymmetric when $\gamma \neq 0$. α_0, α_i, β_j and γ in the equation (2) are the constant, ARCH, GARCH and leverage coefficients, respectively.

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon^2 + \sum_{j=1}^{p} \beta_j h_{t-j} + \sum_{i=1}^{q} \gamma_i I_{t-i} \varepsilon^2$$
$$\text{Where, } I_{t-i} = \begin{array}{ll} 1 & \text{if} \quad \varepsilon_{t-1} \leq 0 \\ 0 & \text{if} \quad \varepsilon_{t-i} > 0 \end{array} \qquad (2)$$

3.2.2 Relationship of trading volume and open interest with volatility. Before using trading volume and open interest as variables in the variance equation, stationarity of each one should be checked using Augmented Dickey Fuller (ADF) and PP (Phillips–Perron) test. If the trading volume and open interest are not found stationary, then both the series should be detrended by regressing them on a deterministic function of time or else they can be made stationary by dividing each point by the average of past 50 points.

As suggested by Chen *et al.* (2001), detrending can be done by allowing both linear (t) and non-linear time trends (t^2).

$$\begin{aligned} Vol_t &= \alpha + \beta_1 t + \beta_2 t^2 + \varepsilon_t \\ OpenInt_t &= \alpha + \beta_1 t + \beta_2 t^2 + \varepsilon_t \end{aligned} \tag{3}$$

In case of non-stationarity, the residuals will be used in the variance equation.

3.2.3 Model with expected and unexpected trading activity variables. GARCH models with volume and open interest as regressors can be carried out to measure their effects on conditional volatility. Both trading volume and open interests are divided into expected and unexpected components to examine whether unexpected component of trading activity carries more information.

The unexpected part is extracted by applying Auto Regression Moving Average (p,q) process to both trading volume and open interest.

$$\begin{aligned} V_t &= \sum_{i=1}^{p} \beta_i V_{t-i} + \sum_{j=1}^{q} \delta_j \varepsilon_{t-j} + \varepsilon_t \\ OpenInt_t &= \sum_{i=1}^{p} \beta_i V_{t-i} + \sum_{j=1}^{q} \delta_j \varepsilon_{t-j} + \varepsilon_t \end{aligned} \tag{4}$$

The estimated trading volume and open interest are the expected components, and the residuals of both the components of equation (4) represent the unexpected part.

So, expanded version of the model using both EV_t (expected volume) and UV_t (unexpected volume), EOI_t (expected open interest) and UOI_t (unexpected open interest) can be included in GARCH and GARCH–GJR (for asymmetry) models which is as follows:

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon^2 + \sum_{j=1}^{p} \beta_j h_{t-j} + \delta_0 EV_t + \delta_1 UV_t + \varsigma_0 EOI_t + \varsigma_1 UOI_t \tag{5}$$

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon^2 + \sum_{j=1}^{p} \beta_j h_{t-j} + \sum_{i=1}^{q} \gamma_i I_{t-i} \varepsilon^2 + \delta_0 EV_t + \delta_1 UV_t + \varsigma_0 EOI_t + \varsigma_1 UOI_t$$

$$\text{Where, } I_{t-i} = \begin{cases} 1 & \text{if} \quad \varepsilon_{t-1} \leq 0 \\ 0 & \text{if} \quad \varepsilon_{t\text{-}i} > 0 \end{cases} \tag{6}$$

δ_0, δ_1, ς_0 and ς_1 in the equations (5) and (6) are the coefficients of expected volume, unexpected volume, expected open interest and unexpected open interest, respectively.

3.2.4 Model with expected and unexpected trading activity variables and asymmetric shocks. An interaction term (the product of dummy and unexpected component) is created to vary with the sign of the shocks. The dummy variable is set to zero for negative shocks (when volume or open interest is below the expected level) or unity for positive shocks (when volume or open interest is higher than the expected level).

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon^2 + \sum_{j=1}^{p} \beta_j h_{t-j} + \delta_0 EV_t + \delta_1 UV_t + \lambda_0(dummy{*}UV_t) + \varsigma_0 EOI_t + \varsigma_1 UOI_t + \lambda_l(dummy{*}UOI_t) \tag{7}$$

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon^2 + \sum_{j=1}^{p} \beta_j h_{t-j} + \sum_{i=1}^{q} \gamma_i I_{t-i} \varepsilon^2 + \delta_0 EV_t + \delta_1 UV_t + \lambda_0(dummy{*}UV_t) + \varsigma_0 EOI_t + \varsigma_1 UOI_t + \lambda_1(dummy{*}UOI_t)$$

$$\text{Where, } I_{t-i} = \begin{cases} 1 & \text{if } \varepsilon_{t-1} \leq 0 \\ 0 & \text{if } \varepsilon_{\text{t-i}} > 0 \end{cases} \tag{8}$$

λ_0 and λ_1 in the equations (7) and (8) are the interaction coefficients of unexpected volume and unexpected open interest, respectively.

4. Results and discussion

4.1 Descriptive analysis of returns, trade volume and open interest

Table I presents the descriptive statistics of futures return, trade volume and open interests. Trade volume and open interests are analyzed after taking the natural logarithm. The mean and standard deviation of returns are presented in percentage. Mean return ranges from 0.03 per cent (cumin and soy oil) to 0.075 per cent (pepper and guar seed). The standard deviation of the futures return is found to be high. Skewness of daily return indicates asymmetry, as it is different from zero. Returns are mostly positively skewed and having longer tails to the right, except in the case of soy oil, whereas trade volume and open interest are negatively skewed. Excess kurtosis of all the series indicates that they are leptokurtic, fat-tailed and sharply peaked. Jerque-Bera (J-B) statistics rejects the null hypothesis of normality. The return data of futures market of cumin are not serially correlated which indicates that the autoregressive integrated moving average (ARIMA) model is not necessary to achieve white noise, while, in other cases, autocorrelation is present. However, squared returns of futures markets are highly autocorrelated, signifying the presence of volatility clustering. ADF and PP tests with constant and trend reject the null hypothesis of unit root. Therefore, returns, trading volume and open interest are stationary (Table I).

4.2 Conditional volatility models – GARCH and GARCH–GJR

Volatility modelling of return is estimated by employing both GARCH and GARCH-GJR models. The estimated results of ARIMA–GARCH and ARIMA–GARCH–GJR are presented in Table II. The ARCH (α) and GARCH (β) parameters determine the short- and long-run persistence of volatility, respectively. The GARCH coefficient (β) is statistically significant for every commodity. The "$\alpha + \beta$" is found to be very high in all the commodities. The highest "$\alpha + \beta$" is in pepper (0.992) followed by guar seed (0.967) and soy oil (0.936). This suggests a high level of volatility persistence. However, volatility is not diverging from mean, as the value of "$\alpha + \beta$" is < 1. GARCH (1, 1) is sufficient to capture the conditional variance except in pepper where more than one lagged residuals is required. The GARCH–GJR model is estimated to capture the asymmetric effect of news or shocks to volatility. It is found that all the commodities have a significant asymmetric coefficient. Cumin and pepper have a positive

Table I.
Descriptive statistics of returns, trade volume and open interest

Var.	Commodity	Mean	SD	Skewness	Kurtosis	Jarque–Bera Stat	LB-Q(6)	LB-Q^2(6)	ADF (constant and trend)	PP (constant and trend)
Return	Cumin	0.03	1.89	0.975	9.690	3,882.90 (0.000)	8.341 (0.214)	20.845 (0.002)	−42.637*	−42.622*
	Soy oil	0.039	1.89	−11.562	3.461	3,622.33 (0.000)	54.058 (0.000)	32.561 (0.000)	−26.021*	−39.964*
	Pepper	0.075	1.763	0.128	4.599	237.35 (0.000)	23.232 (0.001)	206.36 (0.000)	−44.181*	−44.265*
	Guar seed	0.075	1.853	0.335	6.113	945.096 (0.000)	13.628 (0.034)	169.37 (0.000)	−27.282*	−44.186*
Trade volume	Cumin	7.893	0.939	−0.075	2.440	26.89 (0.000)	3,932.7 (0.000)	–	−15.609*	−15.343*
	Soy oil	6.266	1.590	−1.392	4.584	776.44 (0.000)	776.44 (0.000)	–	−7.937*	−20.335*
	Pepper	7.417	1.318	−0.316	2.981	47.159 (0.000)	7,064.3 (0.000)	–	−4.242*	−14.435*
	Guar seed	10.504	1.191	−0.029	2.392	34.779 (0.000)	5,463.3 (0.000)	–	−15.232*	−15.235*
Open interest	Cumin	8.595	0.806	−1.226	5.556	1,004.54 (0.000)	2,869.8 (0.000)	–	−14.079*	−16.200*
	Soy oil	1.943	0.762	−0.226	3.229	9.664 (0.007)	2,065.3 (0.000)	–	−6.192*	−11.251*
	Pepper	8.228	0.860	−0.908	3.451	316.618 (0.000)	4,490 (0.000)	–	−4.252*	−15.816*
	Guar seed	10.621	1.041	−0.921	4.433	508.186 (0.000)	3,214.4 (0.000)	–	−16.681*	−20.319*

Notes: Figures in parentheses are *p*-value at 5 per cent level of significance. LB-Q(k) is the portmanteau statistics to test the joint significance of autocorrelation in the series and squared value of the series. Data in parentheses show *p*-value. * (**) indicate significance at 5 per cent (10 per cent) level; Critical values, ADF and PP (constant and trend); 5 per cent = −2.862, −3.412; 10 per cent= −2.567, −3.127

Table II. Estimates of conditional volatility models

Parameters	GARCH				GARCH–GJR			
	Cumin (ARIMA [0,1,0]–GARCH [1,1])	Soy oil (ARIMA [1,1,1]–GARCH [1,1])	Pepper (ARIMA [2,1,2]–GARCH [2,1])	Guar seed (ARIMA [1,1,1]–GARCH [1,1])	Cumin (ARIMA [0,1,0]–GARCH–GJR [1,1])	Soy oil (ARIMA [1,1,1]–GARCH–GJR [1,1])	Pepper (ARIMA [2,1,2]–GARCH–GJR [2,1])	Guar seed (ARIMA [1,1,1]–GARCH–GJR [1,1])
c	6.9×10^{-4}** (0.085)	4.65×10^{-4} (0.177)	5.63×10^{-4} (0.125)	4.42×10^{-4}* (0.051)	3.37×10^{-4} (0.443)	2.94×10^{-4} (0.571)	4.93×10^{-4} (0.186)	8.71×10^{-4}* (0.020)
AR(1)		−0.872* (0.000)	−1.300* (0.000)	0.030 (0.187)		0.865* (0.000)	−1.291* (0.000)	0.026(0.261)
AR(2)			−0.382* (0.025)				−0.375* (0.026)	
MA(1)		0.906* (0.000)	1.367* (0.000)	−0.001 (0.963)		−0.815* (0.000)	1.361* (0.000)	-9.34×10^{-4} (0.966)
MA(2)			0.469* (0.004)				0.465* (0.003)	
c	7.13×10^{-5}* (0.000)	6.08×10^{-6}* (0.000)	2.51×10^{-6}* (0.000)	9.78×10^{-6}* (0.000)	3.86×10^{-5}* (0.000)	4.73×10^{-6}* (0.000)	2.38×10^{-6}* (0.000)	8.22×10^{-6}* (0.000)
α_1	0.183* (0.000)	0.066* (0.000)	0.149* (0.000)	0.043* (0.000)	0.061* (0.000)	0.065* (0.000)	0.086* (0.003)	0.055* (0.000)
α_2			−0.127* (0.000)				−0.062* (0.035)	
β	0.635* (0.000)	0.870* (0.000)	0.970* (0.000)	0.924* (0.000)	0.778* (0.000)	0.934* (0.000)	0.971* (0.000)	0.933* (0.000)
γ_1					0.135* (0.000)	−0.100* (0.000)	0.141* (0.004)	−0.033* (0.000)
γ_2							−0.147* (0.003)	
AIC	−5.157	−6.272	−5.334	−5.270	−5.168	−6.272	−5.336	−5.273
SC	−5.146	−6.240	−5.311	−5.254	−5.153	−6.235	−5.307	−5.255
HQC	−5.153	−6.259	−5.326	−5.264	−5.162	−6.258	−5.325	−5.266
Log likelihood	4,952.413	2,828.480	5,791.266	5,895.418	4,963.273	2,829.591	5,795.434	5,899.690
$Q^2(4)$	0.515 (0.972)	4.509 (0.341)	5.874 (0.209)	3.182 (0.528)	0.396 (0.983)	2.540 (0.637)	6.501 (0.165)	2.839 (0.725)
ARCH – LM (F-stat)	0.189 (0.828)	0.079 (0.923)	0.294 (0.745)	0.061 (0.805)	0.075 (0.927)	0.886 (0.412)	0.268 (0.764)	0.949 (0.387)
ARCH – LM (TR^2)	0.378 (0.827)	0.159 (0.922)	0.589 (0.745)	0.061 (0.805)	0.152 (0.927)	1.775 (0.411)	0.537 (0.764)	1.900 (0.386)

Notes: Figures in parentheses are *p*-value at 5 per cent level of significance; * indicates significance at 5 per cent (10 per cent) level asymmetry, implying that negative news has a greater impact than the positive news. However, in cases of soy oil and guar seed, the asymmetric coefficient is negative, advocating that negative shocks have lesser effect than the positive shocks. All models of GARCH and GARCH–GJR have also been assessed to check their validity by testing their residuals. The Ljung-Box stat of standardised squared residuals (Q^2) and Lagrange multiplier test are found statistically insignificant. This signifies that the models are well fit and are able to explain the variance (Table II).

4.3 Conditional volatility modelling with expected and unexpected components of trade volume and open interest

Trading volume and open interest have been modelled with ARIMA and found sufficient to capture the conditional return. The residuals of ARIMA model have been extracted and incorporated into the variance equation of return as unexpected components, while the difference between the unexpected and the actual components have been incorporated as the expected component. In addition to GARCH, GARCH–GJR has also been estimated to capture the asymmetric effect of return volatility. The results of GARCH and GARCH–GJR along with the expected and unexpected components of trading volume and open interest are presented in Table III. It is evident in the result that after inclusion of trading volume and open interest in the GARCH equation, the persistence ($\alpha + \beta$) has reduced marginally. The highest reduction is observed in pepper (from 0.992 to 0.601) followed by soy oil (from 0.936 to 0.79), guar seed (from 0.967 to 0.785) and cumin (from 0.818 to 0.702). But the ARCH (α) and GARCH (β) terms have not yet vanished away. It suggests that volatility is more explained by its lagged conditional variances rather than trading volume and open interest. Trading volume and open interest explain conditional variance only to a small extent. The results highlight that the information content of trading volume and open interest are not very much significant. It is also evident that there is a presence of asymmetric effect (γ). Cumin and pepper have a positive asymmetry, which implies that negative news has greater impact on volatility than the positive news. However, in case of soy oil, the asymmetric coefficient is negative, which advocates that negative shocks have lesser effect than the positive shocks. Both the effects of expected and unexpected trading volume and open interest are significant but to a very small extent. Expected trading volume is negative in cumin and soy oil, whereas the relationship is positive in pepper and guar seed. Tauchen and Pitts (1983) argued that a negative relationship exists mainly in immature or expanding markets, whereas a positive relationship is observed in mature markets where trader's participation does not change much or remains almost constant. In an expanding market, the trading volume increases as the number of traders increase. As the average of changes in traders' reservation prices represent the market price changes during a single market clearing, increasing the number of traders in an expanding market means that the inter-differences is mostly negated. Hence, price change or volatility cannot increase while volume has increased. Another explanation for the absence of positive relationship between trading volume and conditional variance of returns in some commodities futures is the absence differential cost of holding long and short positions (Karpoff, 1987). However, this argument is not consistent across the commodities because a positive relationship exists in pepper and guar seed. The unexpected trading volume is positive in almost all the commodities in both GARCH and GARCH–GJR equations. The effect of unexpected part is larger than

Table III. Estimates of conditional volatility with expected and unexpected trading volume and open interest

Parameters	GARCH: Cumin (ARIMA [0,1,0]–GARCH [1,1])	GARCH: Soy oil (ARIMA [1,1,1]–GARCH [1,1])	GARCH: Pepper (ARIMA [2,1,2]–GARCH–GJR [2,1])	GARCH: Guar seed (ARIMA [1,1,1]–GARCH [1,1])	GARCH–GJR: Cumin (ARIMA [0,1,0]–GARCH GJR [1,1])	GARCH–GJR: Soy oil (ARIMA [1,1,1]–GARCH–GJR [1,1])	GARCH–GJR: Pepper (ARIMA [2,1,2]–GARCH–GJR [2,1])	GARCH–GJR: Guar seed (ARIMA [1,1,1]–GARCH–GJR [1,1])
c	-1.71×10^{-4} (0.641)	7.97×10^{-4} (0.281)	1.59×10^{-4} (0.653)	1.62×10^{-4} (0.632)	-1.43×10^{-4}* (0.709)	4.42×10^{-4} (0.273)	1.41×10^{-4} (0.688)	2.28×10^{-4} (0.502)
AR(1)		0.005 (0.999)	0.028 (0.966)	−0.002 (0.999)		0.828* (0.000)	0.033 (0.956)	-6.26×10^{-4} (0.999)
AR(2)			−0.004 (0.993)				-4×10^{-4} (0.992)	
MA(1)		0.005 (0.999)	0.011 (0.987)	−0.002 (0.996)		−0.798* (0.000)	0.011 (0.985)	-4.88×10^{-4} (0.999)
MA(2)			−0.004 (0.993)				−0.005 (0.989)	
c	5.34×10^{-4}* (0.000)	2.58×10^{-4}* (0.000)	3.61×10^{-4}* (0.000)	3.34×10^{-4}* (0.000)	5.0×10^{-4}* (0.000)	4.29×10^{-5}* (0.000)	3.65×10^{-4}* (0.000)	3.46×10^{-4}* (0.000)
α_1	0.158* (0.000)	0.149* (0.000)	0.141* (0.000)	0.131* (0.000)	0.104* (0.000)	0.168* (0.000)	0.096* (0.003)	0.136* (0.000)
α_2			0.037 (0.155)				0.051** (0.082)	
β	0.544* (0.000)	0.590* (0.000)	0.460* (0.000)	0.654* (0.000)	0.555* (0.000)	0.722* (0.000)	0.448* (0.000)	0.645* (0.000)
γ_1					0.100* (0.000)	−0.057* (0.104)	0.088* (0.038)	−0.015 (0.492)
γ_2							−0.024 (0.498)	
EV	-2.01×10^{-5}* (0.000)	-1.45×10^{-5}* (0.005)	3.92×10^{-6} (0.130)	5.66×10^{-6}* (0.000)	-1.97×10^{-5}* (0.000)	-3.14×10^{-6}* (0.008)	7.10×10^{-6}* (0.036)	5.28×10^{-6}* (0.000)
UV	1.02×10^{-4}* (0.000)	5.46×10^{-5} (0.505)	1.01×10^{-4}* (0.000)	1.19×10^{-4}* (0.000)	1.04×10^{-4}* (0.000)	-2.17×10^{-6} (0.391)	9.86×10^{-5}* (0.000)	1.21×10^{-4}* (0.000)
EOI	-3.40×10^{-5}* (0.000)	-4.05×10^{-5}* (0.000)	-3.61×10^{-5}* (0.000)	-3.13×10^{-5}* (0.000)	-3.05×10^{-5}* (0.000)	-4.07×10^{-6}* (0.040)	-3.93×10^{-4}* (0.000)	-3.18×10^{-5}* (0.000)
UOI	7.43×10^{-4}* (0.000)	-1.49×10^{-5} (0.495)	3.96×10^{-5}* (0.000)	-1.22×10^{-5}** (0.072)	4.51×10^{-5}* (0.000)	1.54×10^{-5}* (0.000)	3.54×10^{-4}* (0.000)	-1.34×10^{-5} (0.136)
AIC	−5.343	−5.973	−5.443	−5.407	−5.346	−6.289	−5.449	−5.406
SC	−5.319	−5.920	−5.409	−5.381	−5.320	−6.230	−5.409	−5.378
HQC	−5.334	−5.953	−5.431	−5.397	−5.337	−6.266	−5.434	−5.396
Log Likelihood	5,134.646	2,692.094	5,913.338	6,055.211	5,139.177	2,834.676	5,921.752	6,055.336
$Q^2(4)$	4.471 (0.346)	84.236* (0.000)	5.874 (0.209)	4.024 (0.403)	4.075 (0.396)	0.651 (0.957)	7.489 (0.112)	3.922 (0.417)
ARCH-LM (F-stat)	0.612 (0.542)	51.236* (0.000)	1.146 (0.318)	1.598 (0.202)	0.558 (0.572)	0.096 (0.908)	0.042 (0.837)	1.368 (0.255)
ARCH-LM (TR^2)	1.225 (0.541)	92.234* (0.000)	2.293 (0.317)	3.197 (0.202)	1.118 (0.571)	0.193 (0.908)	0.042 (0.837)	2.737 (0.254)

Notes: Figures in parentheses are *p*-value at 5 per cent level of significance; * indicates significance at 5 per cent (10 per cent) level the expected part. It indicates that price changes occur more due to the flow of private information than predictable information. The results are consistent with the findings of Bessembinder and Seguin (1993), Pati (2008), Javadi (2012) and Sharma *et al.* (1996). However, the results contrast with Lamoureux and Lastrapes (1990) in which the inclusion of volume eliminated the persistence in volatility.

The coefficient estimates of expected and unexpected open interest are also very small but significant. The negative relationship between volatility and expected open interest indicates that when open interest or market depth increases, it lessens volatility. This finding is in line with Bessembinder and Seguin (1993) and Pati (2008). Expected open interest represents the number of traders or the capital affiliated with the market and relates to the speculators or day traders. So, the increase in the trader's participation or capital flow into the market would augment market depth and, consequently, dampen volatility. However, the unexpected part of the open interest, the end-of-the-day positions mainly held by the hedgers, is higher than the expected part, but the sign of coefficient is mostly positive which contrasts with the study of Bessembinder and Seguin (1993). This nature of positive relationship between unexpected open interest and volatility can be because of the fact that the number of hedgers in Indian commodity futures market is very small and, hence, cannot be used as a proxy of amount of uninformed trading.

4.4 Asymmetric effects of unexpected shocks to volume and open interest

An interaction term (the product of dummy and unexpected component) has been created to vary with the sign of the shocks. The dummy variable has been set to zero for negative shocks (when volume or open interest is below the expected level) or unity (when volume or open interest is higher than the expected level). Now, the coefficients associated with the unexpected volume and open interest only capture marginal impact of negative shocks, while the coefficient associated with the interaction term together with the coefficient of unexpected component capture the marginal impact of positive shocks. In both the GARCH and GARCH–GJR models, the interaction term of trading volume emerges to be positive (except in soy oil) which suggests that higher volatility is due to positive shocks to volume (Table IV). This implies that positive private information proxied by positive volume shocks has more impact on volatility than negative shocks. Finally, the impact of volume shocks has been found to be triggered mostly by positive shocks. This is consistent with the results of a study conducted by Bessembinder and Seguin (1993). The coefficients of interaction terms of unexpected open interest have emerged significantly negative in soy oil and positive in pepper at five per cent level of significance in GARCH equation. This implies that unanticipated increase (positive shocks) in open interest is associated with lower volatility in soy oil and higher volatility in pepper. In other cases, the interaction term of open interest is insignificant, at least at the five per cent level of significance. This presents inconclusive evidence of consistent positive or negative asymmetry in unexpected shocks to open interest (Table IV). It is interesting to note that after inclusion of interaction terms, the squared residuals in few cases have been found to have significant autocorrelations (Table IV). This problem is circumvented by augmenting one more lagged GARCH and/or ARCH term[2].

The existence of positive asymmetry indicates that short sales are costly and deters the traders from reacting to information when the effect is to decrease the demands. This

Table IV. Estimates of conditional volatility with expected, unexpected components and asymmetric shocks to trading volume and open interest

Parameters	GARCH: Cumin (ARIMA [0,1,0]–GARCH [1,1])	GARCH: Soy oil (ARIMA [1,1,1]–GARCH [1,1])	GARCH: Pepper (ARIMA [2,1,2]–GARCH GJR [2,1])	GARCH: Guar seed (ARIMA [1,1,1]–GARCH [1,1])	GARCH–GJR: Cumin (ARIMA [0,1,0]–GARCH GJR [1,1])	GARCH–GJR: Soy oil (ARIMA [1,1,1]–GARCH GJR [1,1])	GARCH–GJR: Pepper (ARIMA [2,1,2]–GARCH GJR [2,1])	GARCH–GJR: Guar seed (ARIMA [1,1,1]–GARCH GJR [1,1])
c	4.49×10^{-4}** (0.085)	2.79×10^{-4} (0.515)	-2.3×10^{-4} (0.468)	-1.45×10^{-4} (0.647)	-7.93×10^{-4}* (0.012)	5.02×10^{-4} (0.386)	-8.92×10^{-5} (0.778)	-1.67×10^{-4} (0.595)
AR(1)		0.005 (0.999)	0.007 (0.988)	−0.004 (0.997)		0.005 (0.999)	0.021 (0.898)	−0.003 (0.997)
AR(2)			0.002 (0.998)				−0.005 (0.986)	
MA(1)		0.005 (0.999)	0.007 (0.988)	−0.005 (0.996)		0.005 (0.999)	0.017 (0.916)	−0.008 (0.993)
MA(2)			0.001 (0.998)				−0.006 (0.983)	
c	2.65×10^{-4}* (0.000)	2.35×10^{-4}* (0.000)	2.19×10^{-4}* (0.000)	1.63×10^{-4}* (0.000)	2.56×10^{-4}* (0.000)	2.51×10^{-4}* (0.000)	2.02×10^{-4}* (0.000)	1.58×10^{-4}* (0.000)
α_1	0.174* (0.000)	0.1488* (0.000)	0.128* (0.000)	0.140* (0.000)	0.138* (0.000)	0.150* (0.000)	0.137* (0.000)	0.153* (0.000)
α_2			0.039** (0.076)				0.049** (0.065)	
β	0.548* (0.000)	0.550* (0.000)	0.516* (0.000)	0.515* (0.000)	0.536* (0.000)	0.555* (0.000)	0.429* (0.000)	0.472* (0.000)
γ_1					0.091* (0.000)	0.044 (0.587)	0.058 (0.176)	0.032 (0.269)
γ_2							0.034 (0.329)	
EV	-1.62×10^{-5} (0.000)	-1.38×10^{-5}* (0.000)	-8.8×10^{-6}* (0.004)	-4.34×10^{-6} (0.334)	-1.36×10^{-5}* (0.000)	-1.35×10^{-5}* (0.000)	-2.28×10^{-6} (0.521)	-3.46×10^{-6} (0.597)
UV	6.73×10^{-5} (0.000)	1.18×10^{-5}* (0.000)	9.09×10^{-5}* (0.000)	9.31×10^{-5}* (0.000)	6.51×10^{-5}* (0.000)	2.08×10^{-5}* (0.000)	5.66×10^{-5}* (0.000)	9.07×10^{-5}* (0.000)
Dummy-UV	3.54×10^{-4} (0.000)	-1.93×10^{-5}* (0.000)	1.67×10^{-4}* (0.000)	2.33×10^{-4}* (0.000)	3.48×10^{-4}* (0.000)	-3.44×10^{-5}* (0.000)	2.42×10^{-4}* (0.000)	2.48×10^{-4}* (0.000)
EOI	-1.36×10^{-5} (0.105)	-3.28×10^{-5}* (0.000)	-1.25×10^{-5} (0.111)	-5.73×10^{-6}* (0.000)	-1.46×10^{-5}* (0.006)	-3.26×10^{-5}* (0.000)	-1.73×10^{-5}** (0.057)	-6.01×10^{-6} (0.384)
UOI	-3.13×10^{-5} (0.894)	-2.75×10^{-5}* (0.009)	-2.24×10^{-5}** (0.074)	-3.27×10^{-5}* (0.000)	1.55×10^{-6} (0.956)	-1.40×10^{-5} (0.157)	3.41×10^{-5}* (0.002)	-2.49×10^{-5}* (0.005)
Dummy-UOI	-2.48×10^{-5} (0.287)	-3.37×10^{-5}* (0.002)	7.31×10^{-5}* (0.004)	-3.65×10^{-5} (0.138)	-2.89×10^{-5} (0.121)	-6.22×10^{-5}* (0.000)	4.76×10^{-5}** (0.088)	-4.47×10^{-5}** (0.074)
AIC	−5.428	−6.080	−5.472	−5.446	−5.434	−6.036	−5.472	−5.446
SC	−5.399	−6.016	−5.433	−5.416	−5.402	−5.966	−5.427	−5.413
HQC	−5.418	−6.055	−5.458	−5.435	−5.422	−6.009	−5.456	−5.434
Log likelihood	5216.144	2742.071	5947.140	6098.619	5222.641	2723.330	5949.072	6099.088
$Q^2(4)$	11.154* (0.03)	59.62* (0.000)	16.310* (0.003)	14.859* (0.005)	8.645** (0.071)	70.294* (0.000)	1.823 (0.610)	13.741* (0.008)
ARCH−LM (F-stat)	2.970* (0.052)	33.535* (0.000)	1.392 (0.248)	0.266 (0.765)	2.195 (0.112)	41.582* (0.000)	0.344 (0.708)	1.276 (0.279)
ARCH–LM (TR^2)	5.932* (0.052)	62.595 (0.000)	2.784 (0.248)	0.534 (0.765)	4.387 (0.112)	76.335* (0.000)	0.691 (0.708)	2.552 (0.279)

Notes: Figures in parentheses are p-value at 5 per cent level of significance; * indicates significance at 5 per cent (10 per cent) level eventually reduces the variance of interperiod shifts in transaction supply with respect to that for transaction demand. This phenomenon leads to a positive covariance between trading volume and price changes over the period (Karpoff, 1987). However, a costly short sales argument is valid in stock and bond markets but not in futures markets. In futures markets, the presence of asymmetry in unexpected shocks to the volume is because of the fact that market volatility is affected by market depth. As explained by Bessembinder and Seguin (1993), when trading starts in a day, it begins with a predetermined amount of capital. The market participants like arbitrageurs and other rational traders lessen the effect of order shocks and try to maintain prices as close to their original values. Thus, capital used is dependent on the order flow. Any deviation from the expected order flow decreases the market depth. Positive volume shocks bring in more orders and cause a shortage of capital, whereas negative shocks bring in less order leading to underutilization of capital. Market depth is reduced more during positive volume shocks than negative volume shocks when a shortage of capital poses more threat to market depth.

5. Conclusion and implications

The effect of information flow coupled with trading volume and open interest yields interesting results. After dissecting both trading volume and open interest into expected and unexpected components, they have been included into the variance equations. A positive relationship has been found between volatility and expected trading volume in pepper and guar seed, whereas a negative relationship has been observed in cumin and soy oil. Contrary to this, a positive relationship between unexpected trading volume and volatility has been found in all the commodities except in soy oil where the effect of unexpected trading volume is insignificant. It is noteworthy that the effect of unexpected component is larger than the expected component, suggesting that volatility increases more in response to unanticipated shocks. In case of open interest, a negative relationship has been found in every commodity between volatility and expected open interest, but a positive relationship has been figured out between unexpected open interest and volatility, except guar seed where it is insignificant. In every commodity, the effect of unexpected open interest has been larger than expected component. In addition to this, when an interaction term is added to capture the asymmetric effect, it is found that there is a presence of positive asymmetry in unexpected trading volume in cumin, pepper and guar seed. This implies that positive and unexpected changes in trading volume cause more volatility. Positive asymmetric response in unexpected open interest is present in pepper, but the same has been found to be significantly negative in soy oil. Evidence of asymmetric effects of unexpected shocks to open interest has not been very conclusive. The inclusion of trading volume and open interest in variance equation could not remove the persistence of volatility. MDH says that volume–volatility jointly depends on a common mixing variable, where the rate of information flow is the directing variable. However, the inclusion of both expected and unexpected components of trading volume and open interest could not eat away the whole of GARCH effects. Even shocks to the unexpected trading volume are not a common mixing variable. Hence, trading volume is not a good proxy for the flow of information in the Indian commodity futures markets. The same is also true for open interest. Unexpected component of open interest mainly stands for the number of contracts, which remain open at the end of the day, possibly indicating the small number of hedgers in the Indian commodity futures markets. This is especially true for agro commodity futures. Lesser participation of hedgers may be attributed to the fact that the Indian commodity futures markets are still at a very nascent stage, and the role of futures markets in terms of informational source to spot markets is not obvious to them. On the whole, it can be inferred that open interest and trading volume are not good proxies for informational flow in the Indian commodity markets.

To have a holistic view of complete commodity futures markets, this study can be further extended to futures markets of other commodities to understand the relationship among information flow, shocks and volatility. It may be prudent to conduct both in futures and cash markets to compare the effects of information flow in the futures markets on volatility of the cash markets. One of the key drivers behind the relationship among return volatility, volume and open interest is the maturity of the market itself; therefore, the same study can be carried in different markets based on their maturity. It can be conducted in the Indian and US commodity futures markets, and the results can be compared to know the effect of age of trading on the relationship between volume and volatility. The results of the asymmetric relationship between positive shocks to volume and volatility are dependent on expensive short sale assumptions; hence, the expected outcome of the relationship may differ in the options market because the cost of taking net short position is less.

The present study has implications for both the traders and the policymakers. This study may help identify the behaviour of volatility and the effect of associated factors like trading volume and open interest which cause changes in market dynamics. The relationship among volatility, volume and open interest provides inputs to different traders and market players to stay better acquainted with the dynamics of commodity markets for portfolio formation, as it is evident that information flow proxied by trading volume and open interest explains volatility to a very small extent. Thus, this would guide commodity market players for better portfolio formation and investment strategies. For example, success of hedgers and speculators depends on the forecast ability of futures price movement. The findings between return volatility and information flow (trading volume and open interest) in commodity futures markets reported in this study implies that knowledge of information flow alone does not improve the ability of forecasting the volatility. This study would also help the policymakers to understand volatility of the commodity markets better. For example, it is believed that increased volume in futures markets may lead to increased volatility in both spot and futures markets. This phenomenon does not always hold true in all markets. In this respect, the present study would at least assist policymakers to take decisions of their intervention during excess volatility based not solely on trading volume and open interest but also on other trading and macroeconomic factors. The findings also suggest that the use of trading volume and returns of commodity futures may not be useful in event studies that use trading volume and returns to investigate market reactions to the news of the commodity regarding their production, export and import.

Notes

1. Noise is market activity which is not based on any fundamentals rather caused by some news or shocks. This does not reflect the full market sentiment.
2. Results of GARCH models with more lags are not presented hare. This can be obtained upon request.

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