Price Volatility, Trading Volume and Open Interest: Evidence from Indian Commodity Futures Markets

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Abstract

This paper empirically investigates the relationship between volatility and trading activity including trading volume and open interest, for agricultural, metals, precious metals and energy commodities in Indian commodity derivatives market. Trading volume and open interest are included in this paper to distinguish between speculators/day traders and hedgers. The relationship between volatility and trading activity is more important in emerging market context where derivatives markets are generally criticized for speculative activity and destabilizing effect on spot market. This study uses three different measures of volatility: (1) daily volatility measured by close-to-close returns, (2) non-trading volatility measured by close-to-open returns and (3) trading volatility measured by open-to-close returns. The contemporaneous as well as dynamic relationship between volatility and trading activity are investigated. Following Bessembinder and Senguin (1993), volume and open interest are divided into expected and unexpected components. The contemporaneous relationship between volatility and trading activity is investigated by augmented GARCH model where expected and unexpected components of trading activity (volume and open interest) are used as explanatory variables. This is also an empirical test of the Mixture of distribution hypothesis (MDH) in Indian commodity derivatives markets. The dynamic relationship across conditional volatility from GARCH (1,1), unexpected trading volume and unexpected open interest is examined by Granger Causality test in which trivariate VAR model is used. To obtain additional insights about the interaction between volatility, trading volume and open interest, variance decomposition and impulse response function are employed.

We find positive and significant correlation between volatility and trading volume for all commodities under consideration. It is found that although volume parameters are significant, volatility is mainly explained through its own lagged values. For most of the commodities we find insignificant relationship between volatility and open interest. In Indian commodity futures market trading activity does not proxy for information. The results of dynamic relationship between volatility and trading activity show that only overnight volatility drives the trading volume but not open interest. This result is more prominent in non-agricultural commodities. We also find asymmetric relationship between trading volume and open interest. The lagged open interest affects volume positively but lagged volume affects open interest negatively. This result is also more prominent in case of non-agricultural metals.

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1. Introduction

The informational role of trading activity and its relationship with price changes of financial asset has been widely examined. In particular, futures markets have generated lot of interest in this regard. In futures markets, other than futures trading volume, open interest is an important indicator of futures trading activity and has been generally used as a proxy for hedgers' opinions (Kamara, 1993), hedging demand (Chen et al., 1995), market depth (Bessembinder and Seguin, 1993) and difference in traders' opinions (Bessembinder et al., 1996). Futures trading volume and open interest are supposed to reflect information about aggregate changes in the expectations of the market participants. In an era where the financial markets are witnessing liberalized capital movements, financial reforms, advances in computer technology and information processing, the importance of relationship between trading activity and price changes become vital, especially of emerging markets. Whether the trading volatility, overnight volatility (proxy of global information) or the futures trading activity is the main source of information in the market? What is the relationship (contemporaneous as well as dynamic) across these variables? In emerging markets which are generally characterized by low liquidity, thin trading volume, higher sample average returns, non-normality, better predictability, higher volatility of returns, and small-size sample availability (Antoniou and Ergul; 1997 and Bakaert and Harvey, 1997), the aforementioned issues are more crucial for the participants, financial regulators and in understanding the development of futures markets. Despite the importance of relationship between volatility and trading activity, there is a paucity of research on this topic in emerging commodity futures markets. This paper seeks to empirically investigate the relationship between futures trading activity and price volatility in Indian commodity futures markets.

Several financial theories suggest a positive contemporaneous relationship between return volatility and trading volume. Sequential arrival of information model (Copeland, 1976; Morse, 1980 and Jennings and Barry, 1983) and the mixture of distribution hypothesis, commonly known as MDH hypothesis, (Clark, 1973; Epps and Epps, 1976; Tauchen and Pitts, 1983; and Harris, 1986 Lamoureux & Lastrapes, 1990) explain that the information is disseminated sequentially to the trader, so new information to the market generates both trading volume and price movements. The Mixture of distribution hypothesis (MDH), which is widely used in literature, explains the positive relationship between price volatility and trading volume as they jointly depend on a common factor, information innovation. According to MDH, returns are generated by mixture of distributions and information arrival is the mixing variable. This mixing variable causes momentum in the squared residuals of daily returns and autoregressive nature of the conditional volatility. As information arrival is unobserved, trading volume is considered as the proxy of information flow into the market. Any unexpected information affects both volatility and volume contemporaneously and, therefore volatility and volume are expected to be positively correlated.

Empirically, Andersen (1996), Gallo and Pacini (2000), Kim and Kon (1994), and Lamoureux and Lastrapes (1990, 1994) found evidences consistent with the MDH in the U.S. equity market. In emerging markets, Pyun et al. (2000) investigated 15 individual stocks in the Korean stock market; Brailsford (1996) analyzed the effect of information arrivals on volatility persistence in the Australian stock market and Lange (1999) for the small Vancouver stock exchange. All these studies have found support for the MDH. In general, most of empirical studies, both in the developed and developing equity markets context, have found evidence that the inclusion of trading volume in GARCH model results in a decrease in the volatility persistence or even causes it to vanish. In developed stocks and currency futures markets similar results have been found (Bessembinder and Seguin, 1993; Chen et al.; 1995; Fung and Patterson,1998; Chan et al., 2004)

In futures markets, besides trading volume, open interest is also an important proxy of trading activity. Generally speculators in the market do not hold open position overnight, open interest has been used as a proxy for uninformed trading or hedging activity. Bessembinder and Seguin (1993) suggested that inclusion of open interest with futures trading volume in analyzing return volatility may provide better understanding of price effect of trading activity by informed versus uninformed traders or speculators versus hedgers. Open interest, being a proxy of market depth or hedging activity, is expected to mitigate return volatility (Bessembinder and Seguin; 1993, 1996, Chen et al.; 1995). On the other hand, trading volume being usually associated with speculation or informed trading is expected to be positively correlated with volatility. Bessembinder and Seguin (1993) explained the contemporaneous relationship between return volatility, volume and open interest in various futures markets. They decomposed trading volume and open interest into expected and unexpected components. The unexpected volume and open interest represent speculative and hedging shocks within a trading day respectively. Using expected and unexpected futures trading activity (volume and open interest), Bessembinder and Seguin (1993) examined the relationship in major futures contracts such as currency futures, Treasury bill/bond futures and commodity futures contracts. They found that unexpected volume has a positive impact on volatility, while open interest mitigates volatility. Garcia et al. (1986) studied the lead-lag relationship between volume and volatility in five commodity futures contracts and found the bidirectional relationship between volume and volatility. Najand and Yung (1991) and Foster (1995), using a generalized autoregressive conditional heteroskedasticity (GARCH) model, found a positive relationship between volatility and trading volume in the Treasury bond futures and crude oil futures respectively. Fung and Patterson (1998) found that volume increases volatility, and open interest reduces volatility in currency futures markets.

In an emerging commodity futures markets, Chan et al. (2004) examined the relationship between daily volatility, trading volume and open interest for four futures contracts namely copper, mungbeans, soybeans and wheat traded on Chinese Futures Exchange. They found that volume is positively related with volatility whereas open interest is negatively related to volatility. Liu (2002) used time-stamped transaction data set to understand the micro structure of Chinese soybean futures market and found that the large-volume trading is an important determinant of volatility in the futures market.

Recent studies in the market microstructure suggest that the volatility-volume relationship is more complicated. Many theoretical and empirical studies in this area assert that asset volatility and volume are simultaneously determined and may also have dynamic interactions, such as the bidirectional relationship between price volatility and volume (Garcia et al., 1986; Schwert, 1990; Gallant et al., 1992; Fung and Patterson, 1998). Jennings et al. (1981) found the positive bidirectional causal relationship between volume and absolute price changes. Malliaris and Urrutia (1998) found bidirectional causality between trading volume and future returns (volatility) in six agricultural futures contracts. They also found that the causal relationship is stronger from price to volume. Bhar and Hamori (2005) used GARCH model to understand the dynamic relationship between trading volume and volatility in crude oil futures market and found that the higher order lagged returns affect trading volume.

The dynamic relationship between trading activity and volatility is even more complicated when open interest is used as a proxy of trading activity with futures trading volume. Fung and Patterson (1998) studied the dynamic relationship among trading volume, volatility and open interest in currency futures markets using a vector autoregressive model (VAR) and found that the futures volatility has some predictive power on trading volume but not on open interest. They also found that volume and open interest are not endogenously determined. The dynamic relationship between futures trading activity and futures price volatility has also been studied in the context of examining the effect of derivatives trading on the stock market volatility. Kim et al. (2004) analyzed the effect of trading activity in derivatives (futures and options) of KOSPI 200 on underlying index using VAR model and found bidirectional causality between index volatility and derivatives trading volumes and also between index volatility and open interest.

Despite some research, the dynamic relationship between open interest, trading volume and volatility has not been adequately explored in emerging markets especially in emerging commodity derivatives markets. To fill the research gap, this paper seeks to empirically investigate the contemporaneous and dynamic relationship between futures price volatility and futures trading activity in Indian commodity futures markets. First, we investigate whether there exists GARCH effect in the conditional volatilities of futures returns? If yes then, whether the GARCH effect is diminished or reduced when trading volume and open interest is incorporated as an explanatory variable in the GARCH equation? After examining the contemporaneous relationship between futures volatility and trading activity, we test whether the relationship among trading volume, volatility and market depth is dynamic in nature? If yes, then what is the nature of relationship and speed of adjustment across these variables? We use four agricultural and seven non-agricultural commodities for the analysis. The reason for considering a variety of commodities is to test whether relationship is similar across different commodities or whether different commodities (agricultural and non-agricultural) exhibit different dynamics. In Indian commodity futures markets, the trading volume has been thin (characterized by low trading volume and low trading volatility) and over night volatility is higher than trading volatility (later detailed in the paper), it is important to understand the contemporaneous and dynamic relationship between trading activity and different measures of volatility (trading/overnight). The reason behind higher overnight volatility may be due to the information flow from international market (NYSE or LME). Therefore, we investigate whether there is any difference in relationship between trading activity and volatility when overnight volatility (offshore volatility) and trading volatility (domestic volatility) is considered i.e. is the dynamic relationship consistent with overnight or trading volatility. Three measures of volatility namely daily volatility (close-to-close return volatility), overnight volatility (close-to-open return volatility) and trading volatility (open-to-close return volatility) are considered to examine the dynamic relationship among different measures of volatility and trading activity.

The remainder of the paper is organized as follows. Section 2 presents the data and time series characteristics of returns, volume and open interest. The empirical methodology and results of the relationship among futures price volatility, trading volume and open interest are given in section 3 and the last section concludes.

2. Time Series Characteristics of Returns, Volume and Open Interest

In this paper, four agricultural commodities- Soybean, Maize, Castor seed, and Guar seed, three industrial metals- Aluminum, Copper and Zinc, two precious metals- Gold and Silver, and two energy commodities- Crude oil and Natural gas has been considered. We analyze the near month and next to near month contracts. We prepare the near month futures series and next to near month futures series on rolling basis, i.e. when the near contract approaches maturity, we select data from the next contract. We remove the maturity week data from the near month futures series to remove the maturity bias. Details of the data period and source of data are given in Table 1. The data on opening price, closing price, volume and open interest of agricultural commodities have been taken from NCDEX. For non-agricultural commodities (precious metals, industrial metals and energy commodities), MCX has been chosen because of relatively higher trading volume at MCX. Most of the developed commodity futures markets (US and UK) have non-overlapping trading time and we suspect that price movement in Indian commodity futures market is affected by price movements in these developed markets. Therefore, we compute the trading and non-trading volatility from open-to-close returns and close-to-open returns as proxy for domestic and offshore information, respectively. However, we also compute daily volatility from close-to-close returns for comparative purposes since other studies have been based on close-to-close volatility.

Table 1: Details of Commodity, Data Period and Source

Commodity		Data Period	Data source (Exchange)
	Soy Bean	9/1/2004 to 10/20/2008	NCDEX
	Maize	1/5/2005 to 10/20/2008	NCDEX
	Castor Seed	9/21/2004 to 10/20/2008	NCDEX
Agricultural	Guar Seed	1/1/2004 to 10/20/2008	NCDEX
	Gold	1/1/2004 to 11/20/2008	MCX
Precious Metals	Silver	1/1/2004 to 11/20/2008	MCX
	Aluminium	2/1/2006 to 11/20/2008	MCX
	Copper	6/4/2005 to 11/20/2008	MCX
Metals	Zinc	4/1/2006 to 11/20/2008	MCX
	Crude Oil	4/14/2005to 11/20/2008	MCX
Energy	Natural Gas	7/21/2006to 11/20/2008	MCX

Three daily returns are constructed from the price data: trading-hour, non-trading hour and close-to-close. The trading hour returns (open-to-close) are computed as $\log(P_{c,t}/P_{o,t})$, where $P_{c,t}$ is the closing price at time t and $P_{o,t}$ is the opening price at time t. Similarly, the non-trading-hour returns (close-to-open) are computed as $\log(P_{o,t}/P_{c,t-1})$ and the close-to-close returns are computed as $\log(P_{c,t}/P_{c,t-1})$. Table 2 report basic statistics of trading-hour returns, and non-trading-hour returns. The mean non-trading hour returns are higher than the mean trading hour returns. Furthermore, while the mean trading-hour returns are all positive except agricultural commodities, all commodities have negative non-trading-hour returns. We also find higher volatility of non-trading returns than trading-hour returns which is opposite to the findings in general for trading assets (French and Roll, 1986). It is also observed that autocorrelation is higher for non-trading returns as compared to trading returns. We performed Augmented Dickey and Fuller[3] (1979) unit root test and find that all return series are stationary.

[3]Autocorrelation functions and results of unit root tests on trading, non-trading and close-to-close returns can be obtained from author on request.

Table 2: Summary Statistics: Futures Return

Commodity				Close-to-close		Close-to-open		Open-to-close	
			N	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Agricultural	Soy Bean	Near Futures	929	-0.006	1.006	-0.608	1.156	-0.019	0.450
		Next To Near Futures	1140	0.007	1.085	-0.633	1.233	-0.031	0.462
	Maize	Near Futures	765	0.025	1.160	-0.690	1.417	-0.032	0.533
		Next To Near Futures	943	0.022	1.151	-0.701	1.355	-0.040	0.553
	Castor Seed	Near Futures	757	-0.009	0.868	-0.579	1.035	-0.042	0.494
		Next To Near Futures	942	-0.003	0.947	-0.627	1.120	-0.021	0.426
	Guar Seed	Near Futures	852	-0.128	1.676	-1.346	2.049	0.003	0.449
		Next To Near Futures	1003	-0.136	1.781	-1.460	2.234	-0.016	0.398
Precious Metals	Gold	Near Futures	921	0.051	1.089	-0.560	1.337	0.016	0.173
		Next To Near Futures	1000	0.045	1.050	-0.533	1.301	0.005	0.369
	Silver	Near Futures	928	0.011	1.830	-0.995	2.268	0.018	0.256
		Next To Near Futures	998	0.038	1.765	-0.923	2.204	0.029	0.565
Metals	Aluminium	Near Futures	579	-0.103	1.349	-1.106	1.652	0.009	0.483
		Next To Near Futures	694	-0.075	1.358	-1.060	1.738	0.039	0.595
	Copper	Near Futures	885	-0.003	1.906	-1.186	2.349	0.004	0.336
		Next To Near Futures	927	0.015	1.811	-1.102	2.212	0.015	0.445
	Zinc	Near Futures	549	-0.171	2.007	-1.687	2.491	0.028	0.306
		Next To Near Futures	680	-0.132	1.946	-1.543	2.414	0.035	0.415
Energy	Crude Oil	Near Futures	781	0.032	1.594	-1.044	1.867	0.026	0.320
		Next To Near Futures	944	0.033	1.505	-0.933	1.767	0.032	0.487
	Natural Gas	Near Futures	469	-0.091	2.287	-1.705	2.779	0.006	0.625
		Next To Near Futures	580	-0.101	2.158	-1.607	2.604	0.009	0.883

We obtain the data for trading volume and open interest of all commodities with different maturity (near month futures and next to near month futures) and the basic statistics of trading activity data are given in Table 3. It is interesting to note that in agricultural commodities next to near month futures have higher average volume and average open interest than other commodities, where near month futures have higher average volume and open interest. It is also important to note that in agricultural commodities open interest is higher than the volume. It is not the case with other non-agricultural commodities except Aluminium. In agricultural commodities, Guar seed has highest volume followed by Soybean, Castor seed and Maize in decreasing orders. In non-agricultural commodities, Gold has maximum turnover followed by Silver, Crude oil, Copper, Zinc, Natural gas and Aluminium in decreasing order.

Following Kim (2005), Kim et al. (2004), Fung and Patterson (1999) and Campbell et al. (1993), and in order to eliminate any secular volume growth and to form a stationary time series of trading volume, we transform the trading volume series by incorporating a 50-day backward moving average

$$V_t = \frac{V_t}{\frac{1}{50}\sum_{i=1}^{50} V_{t-i}} \quad [1]$$

where, V_t is the trading volume at time t. The volume series produces a stationary time series that captures the change in the long run movement in trading volume. The same transformation procedure is used for open interest series. We perform Augmented Dickey and Fuller[4] (1979) unit root test on de-trended volume and open interest and find that volume and open interest series are stationary.

Table 3: Summary Statistics: Volume, Open Interest, and Turnover

				Volume		Open Interest		Turnover (in millions rupees)	
Commodity			N	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Agricultural*	Soy Bean	Near Futures	929	15.39	13.19	50.67	21.53	263.96	278.98
		Next To Near Futures	1140	29.74	26.07	93.42	40.07	512.03	537.70
	Maize	Near Futures	765	4.13	7.48	14.42	9.60	30.49	56.78
		Next To Near Futures	943	4.87	10.13	15.96	12.33	37.28	81.75
	Castor Seed	Near Futures	757	0.97	0.78	4.78	2.46	18.07	14.77
		Next To Near Futures	942	1.54	1.43	5.77	2.91	29.44	26.39
	Guar Seed	Near Futures	852	39.64	50.23	46.96	34.14	694.91	933.56
		Next To Near Futures	1003	165.51	125.24	98.90	32.51	3002.96	2397.77
Precious Metals +	Gold	Near Futures	921	27.31	20.65	0.95	0.31	27537.87	24061.62
		Next To Near Futures	1000	3.95	8.98	0.25	0.26	3930.60	9597.97
	Silver	Near Futures	928	0.86	0.53	0.33	0.14	15958.65	11280.00
		Next To Near Futures	998	0.10	0.26	0.07	0.11	1856.18	5383.60
Metals$	Aluminium	Near Futures	579	0.97	0.99	1.69	1.14	115.96	127.44
		Next To Near Futures	694	0.40	0.50	0.83	0.71	48.01	63.16
	Copper	Near Futures	885	31.09	27.00	9.59	5.53	9395.13	7837.78
		Next To Near Futures	927	3.59	5.97	2.04	1.89	1097.79	1847.18
	Zinc	Near Futures	549	39.23	28.71	23.38	14.21	4766.36	3735.21
		Next To Near Futures	680	9.67	11.64	8.03	7.22	1183.73	1450.52
Energy@	Crude Oil	Near Futures	781	3.24	2.66	1.05	0.46	11953.20	12748.66
		Next To Near Futures	944	0.52	0.75	0.29	0.29	1775.92	3189.96
	Natural Gas	Near Futures	469	2.54	2.30	0.92	0.65	872.04	812.01
		Next To Near Futures	580	0.56	0.88	0.36	0.35	192.81	302.92

* For agricultural commodities volume and open interest are in 10,000 MT
+ In case of bullions, volume and open interest for gold are in 1,000 Kg and for silver they are in 1000MT
$ In case of metals, volume and open interest are in 1000MT
@ In case of energy commodities, volume and open interest for crude oil are in 1000,000 BBL and for Natural gas they are in 1000,000 mmBtu

As suggested by Bessembinder and Seguin (1992, 1993), we divide the total trading volume (open interest) into expected and unexpected volume (open interest) using an ARMA[5] Model. The ARMA model is used to fit the detrended volume (open interest) and the predicted part and residuals from the model are obtained. The unexpected volume (open interest) represents daily volume (open interest) shocks within a trading day or the daily volume (open interest) shock.

[4]Autocorrelation functions and results of unit root test on de-trended volume and open interest can be obtained from author on request.

[5]Similar approaches are employed by Board, et al (2001), Kim, et al (2004) to consider the volume decomposed into predictable and unpredictable components. We find the correct model for the series depending upon AIC and SIC criteria. The augmented Dickey-Fuller test reveals that the detrended volume series and open interest are stationary, and thus the series is modeled without differencing.

3. Futures Volatility, Trading Volume and Open Interest: An Empirical Analysis

In this section, firstly we report the results of test on the Mixture of Distribution Hypothesis (MDH) for Indian commodity futures market. We apply GARCH specification to model volatility and the expected and unexpected contemporaneous volume and open interest are used as explanatory variable to test the contemporaneous relationship between conditional volatility and trading activity. Later, we test and report the dynamic relationship between futures volatility, unexpected trading volume/unexpected open interest to understand the causality and speed of adjustment across these variables. The dynamic relationship between these variables is modeled using VAR representation. As stated earlier, we use trading (open-to-close), non-trading (close-to-open) and daily (close-to-close) return volatility measures to understand dynamic relationship and to test MDH.

3.1. Contemporaneous Relationship between Conditional Volatility and Futures Trading Activity: A GARCH Model Approach

In volatility literature, most of the work reports the evidence of GARCH effect in the conditional returns of most of the tradable assets. Recent studies address this issue by adopting GARCH models to eatimate volatility. The GARCH (p,q) model developed by Bollerslev (1986) is explained by

$$r_t = a + \sum_{i=1}^{k} b_i r_{t-i} + \varepsilon_t$$

$$\varepsilon_t \mid \psi_{t-1} \sim N(0, \sigma_t^2) \text{ and} \qquad [2]$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_J \sigma_{t-j}^2 .$$

Where, r_t is the return at time t. The parameter α_i's capture the ARCH effect whereas β_j's capture the GARCH effect. To ensure positive conditional variance, GARCH model has some restriction on the conditional variance parameters. These are- $\alpha_0 \rangle 0$, $\alpha_i \geq 0, \beta_j \geq 0$ and $\alpha_i + \beta_j = 1$. The persistence of the conditional volatility is measured by $\alpha_i+\beta_j$.

The relationship between conditional volatility, trading volume and open interest has been modeled here by modifying the GARCH equation. The expected and unexpected contemporaneous trading volume and open interest are used as explanatory variable. The GARCH equation containing trading volume and open interest as exogenous variable in the volatility equation (Lamoureux and Lastrapes, 1990) is given by-

$$r_t = a + \sum_{i=1}^{5} b_i r_{t-i} + \varepsilon_t$$

$$\varepsilon_t \mid \psi_{t-1} \sim N(0, \sigma_t^2) \text{ and} \qquad [3]$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_J \sigma_{t-j}^2 + \gamma \overline{V}_t + \eta \mu_{v,t} + \lambda \overline{OI}_t + \varphi \mu_{OI,t} .$$

Where, r_t is the return at time t, $\overline{V}_t$ is the expected volume at time t, μ_{vt} is the unexpected volume at time t, $\overline{OI}_t$ is the expected open interest at time t and μ_{OIt} is the unexpected open interest at time t.

The conditional volatility of futures returns (all three measures) is modeled using GARCH (1,1) model. The GARCH parameters estimate of all three return measures are presented in Table 4. For all commodities and for all three volatilities, sum of ARCH and GARCH[6] coefficient ($\alpha_1+\beta_1$) is very high. This shows high volatility persistence is Indian commodity futures. We also estimate the average volatility estimates of daily, overnight and trading volatility estimates from GARCH (1,1) model (not reported here) and find that the mean volatility estimates of overnight volatility are higher than the mean trading volatility and in most of the cases even the mean close-to-close volatility is lower than the overnight volatility. This indicates negative correlation between overnight and trading returns. This result is consistent across the years in the data set. It supports the possibility that in Indian commodity futures markets where trading activity is thin, volatility from developed markets (esp. US and UK) spills over to the Indian market. This finding leads us to consider trading as well as non-trading volatility measures separately to understand the relationship among volatility, volume and open interest.

As discussed, the MDH is tested through GARCH model in which expected and unexpected volume and open interest are used as exogenous variables. Three measures of volatility namely daily volatility (close-to-close), trading volatility (open-to-close) and non-trading volatility (close-to-open) are modeled as GARCH process. The parameter estimates are presented in Table 5(a), Table 5(b) and Table 5(c). It is found that the effect of trading volume on close-to-close volatility is observed for all commodities[7]. In all cases, unexpected volume is significant and positive. Our results are consistent with the findings of Bessembinder and Seguin, (1993). However, in most of the cases, volume and open interest do not completely remove the GARCH effect, but reduce the persistence parameters ($\alpha_1+\beta_1$). This is in contrast to the findings of Lamoureux and Lastrapes (1990) but is consistent with the findings of Najand and Yung (1991) and Foster (1995). It is important to note that we do not find any effect of open interest (expected and unexpected) on volatility. A plausible explanation is that in Indian commodity market the effect of hedging is minimal on price discovery. Alternatively, it may have less power than the speculative activity represented by trading volume. We test the MDH for trading and non-trading volatility. In case of non-trading volatility, we consider one period lagged volume and open interest (expected and unexpected), which also removes the specification bias (Najand and Yung, 1991). It is surprising to note that in both cases, volume and open interest do not reduce the GARCH effect in the volatility. Trading and non-trading volatilities is better explained by their lagged values rather than by volume or open interest.

In agricultural commodities except Soybean, the volume parameter is significant when non-trading volatility is considered. In most of the non-agricultural commodities (except next to near month contracts of Gold, Copper and Natural gas), volume has no explanatory power on volatility. In case of trading volatility, we find that in six out of eleven commodities, parameters of either expected or unexpected volume (Table 5(c)) are significant at 1% significant level but volume is not able to remove or reduce the GARCH effect in volatility. In (almost) all commodities, open interest parameters (expected and unexpected) are not significant in explaining futures volatility.

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[6] The ARCH and GARCH parameters are not significant for Castor seed near month futures and Natural gas (both near month futures and next to near month futures)

[7] In some cases, as reported in table 5 (a) we do not find convergence. However, parameters estimates after 200 iterations are presented.

Table 4: GARCH Parameters of Return Volatility

Commodity			Close-to-Close Returns					Close-to-Open Returns					Open-to-Close Returns				
			Sum Of AR	α	α_1	β_1	$\alpha_1+\beta_1$	Sum Of AR	α	α_1	β_1	$\alpha_1+\beta_1$	Sum Of AR	α	α_1	β_1	$\alpha_1+\beta_1$
Agricultural	Soy Bean	Near Futures	-0.13	0.02+	0.11*	0.88*	0.99	-0.34	0.02*	0.11*	0.88*	0.99	-0.04	0.00+	0.14*	0.85*	0.99
		Next To Near Futures	-0.08	0.01*	0.07*	0.92*	0.99	-0.28	0.02*	0.09*	0.90*	0.99	-0.09	0.00+	0.20*	0.81*	1.01
	Maize	Near Futures	-0.11	0.01*	0.10*	0.90*	1.00	-0.39	0.02+	0.12*	0.87*	1.00	-0.04	0.02*	0.15*	0.79*	0.95
		Next To Near Futures	-0.10	0.04*	0.15*	0.83*	0.98	-0.37	0.10*	0.21*	0.75*	0.95	-0.12	0.00*	0.07*	0.92*	0.99
	Castor Seed	Near Futures	-0.06	0.72*	0.00	0.00	0.00	-0.32	0.07*	0.11*	0.82*	0.93	0.15	0.01+	0.07*	0.87*	0.94
		Next To Near Futures	-0.11	0.02*	0.06*	0.92*	0.98	-0.33	0.04*	0.08*	0.88*	0.96	-0.08	0.00*	0.07*	0.91*	0.98
	Guar Seed	Near Futures	-0.09	0.11*	0.08*	0.88*	0.97	-0.37	0.18*	0.13*	0.83*	0.96	-0.05	0.01*	0.30*	0.73*	1.03
		Next To Near Futures	-0.13	0.09*	0.09*	0.89*	0.98	-0.40	0.13*	0.11*	0.86*	0.97	-0.21	0.01*	0.31*	0.72*	1.03
Precious Metals	Gold	Near Futures	-0.16	0.00*	0.05*	0.95*	1.00	-0.45	0.02*	0.15*	0.84*	0.99	0.00	0.00*	0.19*	0.82*	1.01
		Next To Near Futures	-0.15	0.00*	0.05*	0.95*	1.00	-0.45	0.01*	0.10*	0.89*	1.00	0.13	0.02*	0.82*	0.34*	1.16
	Silver	Near Futures	0.03	0.04*	0.12*	0.88*	1.00	-0.38	0.07*	0.14*	0.85*	0.99	0.08	0.00*	0.18*	0.83*	1.01
		Next To Near Futures	-0.05	0.04*	0.14*	0.86*	1.00	-0.41	0.10*	0.21*	0.78	0.99	0.12	0.00*	0.09*	0.92*	1.01
Metals	Aluminium	Near Futures	-0.03	0.06+	0.09*	0.88*	0.97	-0.41	0.08+	0.10*	0.87	0.97	0.13	0.00*	0.12*	0.88*	1.00
		Next To Near Futures	0.05	0.03*	0.10*	0.89*	0.99	-0.30	0.06*	0.11*	0.87*	0.98	0.01	0.00	0.07*	0.94*	1.01
	Copper	Near Futures	-0.02	0.08*	0.08*	0.90*	0.98	-0.38	0.12+	0.09*	0.88*	0.97	-0.11	0.00+	0.10*	0.90*	1.00
		Next To Near Futures	-0.03	0.07*	0.09*	0.89*	0.98	-0.33	0.15*	0.11*	0.86*	0.96	-0.09	0.00*	0.11*	0.88*	0.98
	Zinc	Near Futures	-0.08	0.24	0.03+	0.91*	0.95	-0.37	4.81*	0.12*	0.03	0.15	0.03	0.00	0.12*	0.88*	0.99
		Next To Near Futures	-0.07	0.17+	0.05*	0.91*	0.96	-0.36	0.27+	0.07*	0.88*	0.95	-0.02	0.00+	0.11+	0.88+	0.99
Energy	Crude Oil	Near Futures	-0.05	0.00	0.03*	0.98*	1.00	-0.39	0.01	0.03*	0.97*	1.00	0.09	0.00*	0.02*	0.96*	0.98
		Next To Near Futures	-0.05	0.01	0.03*	0.97*	1.00	-0.38	0.01	0.04*	0.96*	1.00	0.12	0.00	0.07*	0.93*	1.00
	Natural Gas	Near Futures	0.10	5.42*	0.00	0.00	0.00	-0.31	0.20+	0.06*	0.91*	0.97	-0.06	0.01	0.07*	0.92*	0.99
		Next To Near Futures	-0.02	4.71*	0.00	0.00	0.00	-0.34	0.17	0.05*	0.92*	0.97	0.14	0.01	0.07*	0.92*	0.99

* (+) Significant at 1 (5) % level.

Table 5 (a): GARCH Model with Close-to-Close Volatility and Expected and Unexpected Trading Volume and Open Interest

Commodity			Sum Of AR	α	α_1	β_1	$\alpha_1+\beta_1$	γ	[illegible]	λ	[illegible]
Agricultural	Soy Bean	Near Futures$^{\Delta}$	0.032	0.232	0.282	0.493	0.775	0.000	0.630	0.010	0.000
		Next To Near Futures	-0.048	0.000*	0.278*	0.457*	0.734	0.323*	0.326*	0.000	0.000
	Maize	Near Futures	-0.081	0.235*	0.279*	0.673*	0.952	0.049$^{\#}$	0.251*	0.012	0.000
		Next To Near Futures	-0.086	0.173*	0.213*	0.639*	0.852	0.014	0.491*	0.000	0.000
	Castor Seed	Near Futures$^{\Delta}$	-0.076	0.820	0.078	0.017	0.095	0.208	0.548	0.000	0.000
		Next To Near Futures	0.003	0.169$^{\#}$	0.058$^{\#}$	0.089	0.147	0.494*	0.770*	0.025	0.000
	Guar Seed	Near Futures	0.035	0.519*	0.271*	0.584*	0.855	0.000	1.460*	0.000	0.000
		Next To Near Futures	0.010	0.778*	0.121*	0.000	0.121	1.841*	3.239*	0.000	0.000
Precious Metals	Gold	Near Futures$^{\Delta}$	0.011	0.063	0.111	0.037	0.148	0.633	0.682	0.036	0.000
		Next To Near Futures	-0.066	0.002*	0.050*	0.951*	1.002	0.000	0.014*	0.000	0.000
	Silver	Near Futures$^{\Delta}$	0.047	0.141	0.138	0.008	0.146	1.816	1.877	0.000	0.004
		Next To Near Futures	-0.017	0.043*	0.133*	0.863*	0.996	0.000	0.064*	0.000	0.000
Metals	Aluminium	Near Futures$^{\Delta}$	0.039	0.080	0.040	0.000	0.040	1.673	1.760	0.017	0.002
		Next To Near Futures	0.047	0.911*	0.152*	0.390*	0.542	0.000	0.973*	0.000	0.000
	Copper	Near Futures$^{\Delta}$	-0.011	2.505	0.061	0.081	0.142	0.001	1.843	0.000	0.871
		Next To Near Futures$^{\Delta}$	0.081	1.584	0.230	0.279	0.509	0.076	0.622	0.000	0.006
	Zinc	Near Futures	-0.006	1.310*	0.000	0.025*	0.025	2.470*	3.029*	0.000	0.000
		Next To Near Futures$^{\Delta}$	0.028	0.015	0.002	0.006	0.008	5.430	5.508	0.000	0.000
Energy	Crude Oil	Near Futures	0.076	0.000*	0.116*	0.000	0.116	2.476*	2.450*	0.000	0.000
		Next To Near Futures	0.041	0.922*	0.156*	0.148*	0.305	1.407*	2.298*	0.000	0.000
	Natural Gas	Near Futures	-0.012	0.866*	0.000	0.000	0.000	5.123*	5.614*	0.000	0.000
		Next To Near Futures	-0.040	3.006*	0.000	0.000	0.000	1.808*	2.118*	0.083	0.000

$^{\Delta}$ Did not converge and value after the last iteration is presented.

*, #, $ significant at 1, 5 and 10% level respectively

Table 5 (b): GARCH Model with Overnight Volatility (Close-to-Open) and Expected and Unexpected Trading Volume and Open Interest

Commodity			Sum Of AR	α	α_1	β_1	$\alpha_1+\beta_2$	γ	[illegible]	λ	[illegible]
Agricultural	Soy Bean	Near Futures	-0.323	0.029*	0.093*	0.886*	0.978	0.000	0.079$^{\#}$	0.000	0.000
		Next To Near Futures	-0.306	0.029	0.084*	0.900*	0.984	0.010	0.013	0.010	0.000
	Maize	Near Futures	-0.377	0.000*	0.092*	0.885*	0.977	0.044*	0.051*	0.000	0.007
		Next To Near Futures	-0.355	0.083$^{\#}$	0.127*	0.812*	0.939	0.000	0.212*	0.016	0.000
	Castor Seed	Near Futures	-0.317	0.148*	0.099*	0.845*	0.943	0.000	0.082*	0.000	0.013
		Next To Near Futures	-0.297	0.045*	0.065*	0.896*	0.961	0.000	0.062	0.000	0.246$^{\$}$
	Guar Seed	Near Futures	-0.327	0.219*	0.123*	0.827*	0.951	0.000	0.377*	0.000	0.000
		Next To Near Futures	-0.341	0.034	0.076*	0.887*	0.963	0.072	0.417*	0.052	0.000
Precious Metals	Gold	Near Futures	-0.396	0.019*	0.127*	0.865*	0.992	0.000	0.000	0.000	0.000
		Next To Near Futures	-0.399	0.000	0.096*	0.902*	0.998	0.008*	0.000	0.000	0.000
	Silver	Near Futures	-0.395	0.116	0.146*	0.848*	0.993	0.000	0.019	0.000	0.000
		Next To Near Futures	-0.397	0.129*	0.249*	0.749	0.998	0.000	0.037$^{\#}$	0.000	0.000
Metals	Aluminium	Near Futures	-0.352	0.089$^{\$}$	0.097*	0.873*	0.970	0.000	0.039	0.000	0.000
		Next To Near Futures	-0.323	0.067*	0.070*	0.909*	0.979	0.000	0.087*	0.000	0.068
	Copper	Near Futures	-0.337	0.000*	0.088*	0.883*	0.972	0.000	0.000	0.118*	0.000
		Next To Near Futures	-0.318	0.143$^{\#}$	0.106*	0.857*	0.963	0.005	0.041	0.000	0.000
	Zinc	Near Futures	-0.372	5.378*	0.117$^{\#}$	0.014	0.132	0.000	0.272	0.000	0.000
		Next To Near Futures	-0.395	0.419$^{\#}$	0.084$^{\#}$	0.841$^{\#}$	0.925	0.000	0.113	0.000	0.000
Energy	Crude Oil	Near Futures	-0.334	0.000*	0.034*	0.966*	1.001	0.000	0.000	0.007	0.000
		Next To Near Futures	-0.323	0.002	0.045*	0.954*	0.999	0.000	0.000	0.010	0.000
	Natural Gas	Near Futures	-0.373	0.203	0.048$^{\#}$	0.931*	0.980	0.000	0.200	0.000	0.000
		Next To Near Futures	-0.369	0.000	0.000	1.000*	1.000	0.011	0.290*	0.000	0.134

*, #, $ significant at 1, 5 and 10% level respectively

Table 5 (c): GARCH Model with Trading (Open-to-Close) Volatility and Expected and Unexpected Trading Volume and Open Interest

Commodity			Sum Of AR	α	α_1	β_1	$\alpha_1+\beta_2$	γ	[illegible]	λ	[illegible]
Agricultural	Soy Bean	Near Futures	-0.008	0.001	0.136*	0.843*	0.979	0.003	0.003	0.000	0.000
		Next To Near Futures	-0.070	0.000	0.210*	0.783*	0.993	0.004$	0.004$	0.000	0.009
	Maize	Near Futures	-0.101	0.113*	0.117*	0.000	0.117	0.085*	0.051*	0.000	0.000
		Next To Near Futures	-0.068	0.009*	0.069*	0.909*	0.978	0.000	0.021*	0.000	0.003
	Castor Seed	Near Futures	0.020	0.009	0.071*	0.872*	0.943	0.002	0.000	0.000	0.000
		Next To Near Futures	0.033	0.005*	0.073*	0.904*	0.976	0.000	0.001	0.000	0.000
	Guar Seed	Near Futures	-0.077	0.000	0.280*	0.746*	1.026	0.005	0.010	0.000	0.000
		Next To Near Futures	-0.029	0.000	0.246*	0.737*	0.982	0.009*	0.014#	0.000	0.000
Precious Metals	Gold	Near Futures	0.020	0.002#	0.197*	0.818*	1.014	0.000	0.001*	0.000	0.000
		Next To Near Futures	0.096	0.008*	0.345*	0.666*	1.011	0.001*	0.000	0.000	0.000
	Silver	Near Futures	0.061	0.013*	0.179*	0.800*	0.980	0.000	0.005*	0.000	0.000
		Next To Near Futures	-0.019	0.000	0.092*	0.912*	1.004	0.001*	0.000	0.000	0.000
Metals	Aluminium	Near Futures	0.041	0.003	0.113*	0.882*	0.995	0.003	0.009$	0.000	0.000
		Next To Near Futures	0.020	0.000	0.082*	0.920*	1.001	0.003*	0.013*	0.000	0.000
	Copper	Near Futures	-0.095	0.000	0.083*	0.884*	0.967	0.000	0.011*	0.002#	0.000
		Next To Near Futures	-0.041	0.003	0.109*	0.879*	0.987	0.001	0.000	0.000	0.000
	Zinc	Near Futures	-0.075	0.016*	0.177*	0.773*	0.950	0.000	0.016*	0.006	0.000
		Next To Near Futures	-0.014	0.001	0.117*	0.869*	0.986	0.004	0.000	0.000	0.000
Energy	Crude Oil	Near Futures	0.003	0.000	0.019*	0.961*	0.980	0.001*	0.000	0.000	0.000
		Next To Near Futures	-0.007	0.000	0.062*	0.938*	1.000	0.001$	0.000	0.000	0.000
	Natural Gas	Near Futures	-0.046	0.003	0.059*	0.931*	0.990	0.003	0.018	0.004	0.017
		Next To Near Futures	-0.011	0.001	0.038*	0.962*	1.001	0.000	0.035*	0.002	0.000

*, #, $ significant at 1, 5 and 10% level respectively

If the information is not exogenous or prices and volume are jointly determined, the augmented GARCH model may have some simultaneity bias. Following Najand and Yung (1991), the simultaneity bias in the augmented GARCH model is removed through lagged expected and unexpected volume and open interest in place of contemporaneous values. We find that there is no significant change in the results. Results of the GARCH model with two lags[8] of unexpected volume and open interest are represented in Appendix 1.

Results on the test of MDH hypothesis in Indian commodity futures markets lead us to the interpretation that trading volume in Indian commodity market does not proxy for information but may provide dispersion or quality of information signals (Blume et al., 1994). From the results, it can be inferred that trading volume and open interest are inappropriate surrogate for the rate of information arrival in the case of Indian commodity futures market. More importantly in Indian commodity market, open interest which is generally used as a proxy of market depth has no significance in explaining daily volatility. The testes reported so far are the test of whether volume or open interest represents a proxy for information rather than the volatility itself being a proxy of information (Foster, 1995). These tests do not test the dynamic relationship among volatility and trading activities. However, as explained earlier, the relationship among volatility, volume and open interest may be dynamic, which may be explained through VAR model.

It is interesting to note that the number of cases of significant volume parameters are very high in case of close-to-close return volatility as compared to other two volatility measures. It can be argued that the non-trading volatility is exogenous (volatility spillover from other developed markets) and this volatility may cause volume in the next trading day. It is likely that non-trading

[8] We experiment with different lags but the results are robust across different lag lengths.

volatility (offshore volatility) is the major source of information for speculation in emerging market like India. This may be the reason why we find negative correlation between non-trading and trading returns for most of the commodities. Indian market is thin in terms of market depth and participation of hedgers is limited and this may result in limited trading activity (price correction or information dissipation) and hence limited trading volume. Give this scenario it is possible that trading volatility is not related to trading activity. However, the assumption of next day trading volume caused by overnight volatility and negative correlation between non-trading and trading returns may be the reasons for the significant relationship among close-to-close volatility and trading volume. We investigate these issues further through lead-lag relationship between trading activity and volatility.

3.2 Dynamic Relationship between Volatility, Volume and Open Interest: A VAR Modeling Approach

We use a vector autoregressive (VAR) model to investigate dynamic (lead-lag) relationship among futures volatility, trading volume, and open interest. The advantage of the VAR system is that it estimates unrestricted reduced form equations with uniform sets of the lagged dependent variables of each equation as regressors. This approach sets no restrictions on the structural relationships of the economic variables, and hence avoids mis-specification problems. It is also suitable when endogenous variables are autocorrelated. It also helps in examining the speed of information transformation among endogenous variables and its lags. The VAR model that analyzes the dynamic relationship among price volatility, volume and market depth for the commodity futures markets is expressed as follows:

$$
\begin{aligned}
\sigma_t^2 &= a_{1,t} + \sum_{i=1}^{k} b_{1,t}\sigma_{t-i}^2 + \sum_{i=1}^{k} c_{1,t}\mu_{v,t-i} + \sum_{i=1}^{k} d_{1,t}\mu_{OI,t-i} \\
\mu_{v,t} &= a_{2,t} + \sum_{i=1}^{k} b_{2,t}\sigma_{t-i}^2 + \sum_{i=1}^{k} c_{2,t}\mu_{v,t-i} + \sum_{i=1}^{k} d_{2,t}\mu_{OI,t-i} \qquad [4] \\
\mu_{OI,t} &= a_{3,t} + \sum_{i=1}^{k} b_{3,t}\sigma_{t-i}^2 + \sum_{i=1}^{k} c_{3,t}\mu_{v,t-i} + \sum_{i=1}^{k} d_{3,t}\mu_{OI,t-i}
\end{aligned}
$$

Where, σ_t^2 is conditional volatility estimated from GARCH (1,1) model, $\mu_{v,t}$ is the unexpected volume obtained from ARMA model, and $\mu_{OI,t}$ is the unexpected open interest obtained from ARMA model. The 5 lag length of each endogenous variable is selected to remove any day of the week effect in the variables.

Sims (1972, 1980) and Abdullah and Rangazas (1988) suggested that the variance decomposition and orthogonalized impulse response function of the forecast error is advisable while analyzing the dynamic relationship between variables because it may be misleading to rely solely on the statistical significance of economic variables as determined by VAR model or Granger causality test. Therefore, we estimate the variance decomposition of the forecast error and orthogonalized Impulse response function of the forecast error for each endogenous variable. The variance decomposition of the forecast error gives the percentage of variation in each variable (e.g. volume) that is explained by other variables in the system (e.g. volatility or open interest). The orthogonalized impulse response functions gives the impact of shock in each variable (e.g. open, interest or volume) at a particular time on other variables in the system (e.g. volatility) to a specified length in future, which is serially and contemporaneously uncorrelated.

3.2.1 Granger Causality Test

We use trivariate VAR specification to estimate the dynamic relationship among volatility, trading volume and open interest. Three endogenous variables considered for the VAR analysis are volatility, estimated from GARCH (1,1) model, unexpected volume obtained from ARMA model and unexpected open interest also obtained from ARMA model. In the VAR model, five lag lengths of each endogenous variable are considered to remove any day of the week effect in the model. Ganger causality test is used for testing the causality between volatility and unexpected volume, and volatility and unexpected open interest. Table 6 (a) and 6 (b) present the Chi-square test statistics of Granger causality tests for the trivariate VAR system. We separately consider the trading volatility (open-to-close), non-trading volatility (close-to-open) and close-to-close return volatility. Table 6 (a) gives the Chi-square test statistics of the test that volatility is not affected by lagged volume or open interest (null hypothesis) and Table 6 (b) shows the same statistics of the test that volume (open interest) is not affected by lagged volatility.

The results given in Table 6 (a) confirm that the causality runs from unexpected trading volume to volatility for all commodities when close-to-close and close-to-open volatility measures are considered. Similar results are also found when next to near month futures are analyzed. However, when open-to-close volatility is considered, we find the similar causality from unexpected volume to volatility only in Maize, Guar seed, Silver and Copper near month futures and in Maize, Guar seed, Crude oil and Natural gas in next to near month futures. Other commodities do not show the effect of lagged volume on trading volatility. The effect of lagged unexpected open interest on volatility is also analyzed. In near month futures, unexpected open interest Granger causes volatility (close-to-close and close-to-open) for all agricultural commodities. However, we do not find any such causality in precious metals. In case of Gold, the unexpected open interest Granger causes trading volatility in both near month and next to near month contracts. Similar causality is also found in case of energy commodities and Aluminum next to near month futures contracts.

We also analyze the test of Granger causality running from volatility to unexpected trading volume and volatility to unexpected open interest (Table 6 (b)). In agricultural commodities, mostly all three measures of volatility Granger causes volume either in near month or next to near month futures contracts. In Gold, unexpected trading volume and unexpected open interest is not Granger caused by any volatility measure. In case of silver, only unexpected trading volume in near month futures is Granger caused by volatility (all three). In case of metals and energy commodities, effect of volatility on unexpected trading volume (open interest) is negligible.

Table 6 (a): Granger Causality Test of Effect of Volume and Open Interest on Volatility by Applying Trivariate VAR Model for Causal Relations

	Near Month Futures						Next To Near Month Futures					
	Close-To-Close Volatility		Close-To-Open Volatility		Open-To-Close Volatility		Close-To-Close Volatility		Close-To-Open Volatility		Open-To-Close Volati	
	Volume	Open Interest	Volume	Open Interest	Volume	Open Interest	Volume	Open Interest	Volume	Open Interest	Volume	Open Inter
Soy Bean	85.06*	11.22#	82.38*	15.01*	2.67	2.37	63.08*	21.07*	41.97*	23.79*	4.62	13.
Maize	140.77*	5.86	49.87*	7.60	13.53#	0.90	180.55*	13.03#	78.25*	4.28	12.96#	2
Castor Seed			93.10*	5.15	3.21	10.84$	390.84*	23.62*	290.90*	23.00*	1.35	3
Guar Seed	260.24*	15.24*	195.86*	11.76#	25.21*	2.34	797.01*	12.96#	364.95*	12.39#	61.12*	19.
Gold	76.26*	0.63	62.08*	1.70	1.40	14.04#	11.19#	1.79	10.63$	3.06	4.23	16.
Silver	42.80*	0.16	42.42*	0.43	16.74*	3.17	2.97	3.09	1.14	0.88	2.40	6
Aluminium	128.40*	7.97	60.67*	5.02	4.32	9.51	60.10*	36.33*	34.73*	66.49*	3.25	15.
Copper	83.62*	18.30*	52.24*	8.48	25.95*	3.87	15.88*	1.55	5.25	1.25	3.19	0
Zinc	100.62*	10.49$	62.62*	26.10*	6.95	5.00	23.89*	1.66	14.80#	3.13	1.16	1
Crude Oil	69.76*	18.62*	52.39*	13.50#	0.95	6.12	19.67*	2.14	19.69*	1.57	21.87*	26.
Natural Gas			48.66*	14.12#	2.99	3.28			56.24*	16.87*	37.41*	27.

*, #, $ significant at 1, 5 and 10% level respectively

Table 6 (B): Granger Causality Test of Effect of Volatility on Volume and Open Interest by Applying Trivariate VAR Model for Causal Relations

	Near Month Futures						Next To Near Month Futures					
	Close-To-Close Volatility		Close-To-Open Volatility		Open-To-Close Volatility		Close-To-Close Volatility		Close-To-Open Volatility		Open-To-Close Volati	
	Volume	Open Interest	Volume	Open Interest	Volume	Open Interest	Volume	Open Interest	Volume	Open Interest	Volume	Open Inter
Soy Bean	3.98	1.87	5.37	2.12	2.89	5.25	29.74*	1.89	26.31*	2.83	4.34	2
Maize	11.07#	17.59*	19.59*	7.62	76.11*	8.56	9.74$	33.21*	10.41$	30.47*	3.83	30.
Castor Seed			15.00*	19.84*	13.14#	19.43*	8.19	11.22#	9.47$	13.63#	1.93	2
Guar Seed	15.10*	21.02*	10.72$	16.76*	26.24*	94.68*	30.60*	3.93	13.47#	5.15	61.59*	8
Gold	6.31	6.13	9.10	6.26	0.84	0.87	2.83	2.07	2.48	2.78	3.31	2
Silver	25.27*	3.86	26.06*	3.90	17.10*	5.65	1.67	0.29	2.02	0.56	1.10	0
Aluminium	16.34*	9.20	14.49#	4.86	5.89	2.43	5.17	24.22*	3.89	47.43*	2.19	7
Copper	10.10$	3.65	7.62	5.36	9.21	4.01	3.51	2.56	4.22	2.60	2.97	2
Zinc	4.10	2.33	2.45	2.07	8.83	2.97	5.93	7.25	5.67	7.28	2.52	1
Crude Oil	1.71	8.45	1.40	6.41	2.69	2.42	8.71	5.88	10.95$	8.01	11.85#	9.
Natural Gas			1.67	26.10*	4.40	6.36			6.82	9.03	8.61	13.

*, #, $ significant at 1, 5 and 10% level respectively

The results of the Granger causality test is represented in Table 7 (a)-7(c). Table 7 (a), Table 7 (b), and Table 7 (c) present the VAR estimates of volume, open interest with daily (close-to-close) volatility, non-trading (close-to-open) volatility and trading (open-to-close)volatility respectively. Results of VAR models suggest that all three measures of volatility are highly autoregressive in nature, which is in accordance with the general characteristics of volatility. We also find the parameter estimates of one day lagged unexpected volume in volatility equation is significant and positive. This result is consistent in case of all commodities and for both near and next to near month futures contracts. Our results are consistent with the results of Bessembinder and Seguin (1993). However, we do not find any significant effect of unexpected open interest on volatility on all commodities except for Maize, Guar seed, Gold, Aluminium and Crude. In some cases the effect is positive (Maize, Gold and Crude) and in others negative (Guar seed, Aluminium).

While analyzing the effect of volatility on volume, we found that among all three measures of volatility, the lagged overnight volatility is mainly driving the futures trading volume. Other two measures, trading and daily (based on close-to-close returns) volatility do not have strong effect on volume. Open interest on the other hand is not affected by any measure of volatility in most of the commodities except some agricultural commodities (Guar seed and Maize). Interestingly, we find that the unexpected volume is positively affected by lagged unexpected open interest of all commodities and this effect is significant in all four agricultural commodities and Gold. This result is also consistent across all volatility measures and near month and for next to near month contracts. However, the lagged unexpected volume affects unexpected open interest of non-agricultural commodities and in most of the cases, it is negative. This result is more prominent in next to near month contract and when trading volatility is considered as third endogenous variable. It can be concluded that the asymmetric relationship between volume and depth is not endogenously determined in Indian commodity derivatives market. We also analyze the variance decomposition and impulse response function of each variable. It is possible that some variables that may not be statistically significant may have economic significance (Sims, 1980)

3.2.2. Variance Decomposition

Under VAR system, the variance decomposition explains the relative impact of one variable on another variable. This analysis measures the percentage of the forecast error of one endogenous variable that is explained by other variables. The main aim of this analysis is to check the results of Granger causality test and VAR parameters. We are also trying to compare the economic significance of three measures of volatility on trading activity and vice versa. Results of the variance decomposition for volatility, volume and open interest are reported in Table 8 (a) to 8 (c). Table 8 (a) represents the relative importance of volume and open interest on all three measures of volatility.

Table 7 (a) VAR Model with Close-To-Close Return Volatility, Volume and Open Interest

Volatility

	a_1	$b_{1,1}$	$b_{1,2}$	$b_{1,3}$	$b_{1,4}$	$b_{1,5}$	$c_{1,1}$	$c_{1,2}$	$c_{1,3}$	$c_{1,4}$	$c_{1,5}$	$d_{1,1}$	$d_{1,2}$	$d_{1,3}$	$d_{1,4}$	$d_{1,5}$
Soy Bean	0.02$^{\#}$	0.91*	0.17*	-0.01	-0.19*	0.11*	0.11*	0.03$^{\#}$	-0.10*	-0.01	0.01	-0.07	0.00	-0.05	0.07$^{\#}$	0.01
Maize	0.13*	0.94*	0.05	-0.04	0.00	0.03	0.07*	0.01	-0.06	0.02*	-0.02*	0.02*	0.03*	-0.04	0.01	0.03
Castor Seed	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
Guar Seed	0.10*	0.91*	0.00	0.06	0.09$^{\#}$	-0.10*	0.48*	0.09	-0.27*	0.04	0.00	-0.89*	0.11*	-0.22*	-0.21*	0.04
Gold	0.10*	1.06*	0.10$^{\#}$	-0.21*	0.05	-0.01	0.06*	0.01	-0.03	-0.01	0.00	-0.02	0.00	0.00	-0.01	-0.02
Silver	1.45*	1.05*	-0.10*	0.23*	-0.21*	-0.01	0.58*	0.00	-0.11	0.20*	-0.12	-0.33	-0.10	0.10	-0.06	-0.09
Aluminium	0.08*	1.04*	-0.14$^{\#}$	0.07	0.07	-0.06	0.15*	-0.01	-0.21$^{\#}$	0.01	-0.01	-0.21	0.01	-0.09	-0.05	-0.05
Copper	0.10*	0.91*	0.15*	-0.11$^{\#}$	0.08$^{\$}$	-0.06$^{\$}$	0.28*	0.03	-0.60*	-0.04	-0.04	0.23	-0.05	-0.11	0.12	-0.06
Zinc	0.31*	0.98*	0.04	-0.11$^{\$}$	0.04	0.00	0.15*	0.00	-0.10	-0.02	-0.02	0.17	-0.02	-0.12$^{\$}$	-0.01	-0.08
Crude Oil	0.03	1.05*	-0.10$^{\$}$	0.05	0.00	0.01	0.07*	-0.02$^{\#}$	-0.11*	0.01	0.00	0.10*	0.00	0.00	0.01	-0.04
Natural Gas	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--

Volume

	a_2	$b_{2,1}$	$b_{2,2}$	$b_{2,3}$	$b_{2,4}$	$b_{2,5}$	$c_{2,1}$	$c_{2,2}$	$c_{2,3}$	$c_{2,4}$	$c_{2,5}$	$d_{2,1}$	$d_{2,2}$	$d_{2,3}$	$d_{2,4}$	$d_{2,5}$
Soy Bean	0.04	-0.05	0.01	0.05	-0.08	0.04	-0.10*	-0.06$^{\$}$	-0.04	0.00	0.02	0.56*	-0.03	0.20$^{\#}$	0.20$^{\#}$	-0.10
Maize	-0.87*	-0.02	-0.33	0.36	-0.02	-0.11	-0.03	0.00	-0.01	-0.01	0.01	0.74*	-0.01	0.07	0.14	0.08
Castor Seed	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
Guar Seed	-0.03	-0.12$^{\#}$	-0.03	0.19*	-0.07	0.04	-0.12*	0.04	-0.02	0.00	0.01	0.60*	0.04	-0.02	-0.03	-0.17
Gold	-1.85*	-0.05	-0.12	0.12	0.13	-0.10	-0.06	0.05$^{\$}$	0.01	0.01	-0.18*	0.41*	0.03	0.12	0.24$^{\#}$	0.11
Silver	-2.48*	-0.01	0.02	-0.02	-0.01	0.01	-0.02	0.05	0.13	0.07$^{\#}$	-0.08$^{\#}$	0.21	-0.10*	-0.03	0.23$^{\#}$	0.19$^{\$}$
Aluminium	-0.11	0.02	-0.07	-0.12	-0.01	0.05	-0.07	-0.04	0.48$^{\$}$	0.00	-0.06	0.15	-0.11*	-0.06	0.30	-0.27
Copper	-0.06$^{\$}$	-0.05	0.08$^{\$}$	0.01	0.02	-0.05	-0.09*	-0.02	0.43*	-0.04	-0.11*	0.30	-0.02	0.22	0.19	-0.07
Zinc	-0.85*	-0.24$^{\#}$	0.22	-0.02	0.03	-0.01	-0.06	0.00	0.38$^{\#}$	0.05	0.06	-0.04	0.03	0.33$^{\$}$	0.11	0.29
Crude Oil	-0.94*	-0.14	0.15	-0.14	0.22	-0.08	0.05	0.00	0.45*	0.09*	-0.10*	0.12	0.01	-0.12	0.21	-0.13
Natural Gas	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--

Open Interest

	a_3	$b_{3,1}$	$b_{3,2}$	$b_{3,3}$	$b_{3,4}$	$b_{3,5}$	$c_{3,1}$	$c_{3,2}$	$c_{3,3}$	$c_{3,4}$	$c_{3,5}$	$d_{3,1}$	$d_{3,2}$	$d_{3,3}$	$d_{3,4}$	$d_{3,5}$
Soy Bean	0.00	-0.01	-0.04	0.02	0.03	0.00	0.00	0.02$^{\$}$	-0.02	0.00	0.00	-0.02	0.01	-0.03	-0.02	-0.03
Maize	-0.02	0.03	0.03	0.01	0.01	-0.07$^{\#}$	0.00	0.01	-0.03	0.00	-0.01	-0.02	0.00	0.00	-0.01	0.00
Castor Seed	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
Guar Seed	-0.06*	-0.01	-0.03	0.04$^{\$}$	-0.04	0.05	0.00	0.01	-0.07$^{\$}$	0.01	0.01	-0.04	0.02	-0.06	-0.04	-0.04
Gold	0.02	-0.04	0.03	0.01	-0.05	0.04	0.00	0.00	-0.02	-0.01	0.01	-0.02	0.00	0.00	-0.01	0.00
Silver	-0.04	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	0.00	-0.01	0.00	-0.03	0.00	-0.01	0.03	0.01
Aluminium	0.00	0.01	0.03	-0.04$^{\$}$	0.02	-0.02	0.01	0.00	0.00	0.01	-0.01	0.04	0.01	-0.03	0.02	-0.06
Copper	0.00	-0.01	0.01	-0.01	0.01	0.00	-0.01	0.01	0.00	0.01	0.00	0.01	-0.01	0.01	0.02	0.08$^{\#}$
Zinc	0.01	0.00	-0.04	0.01	0.06	-0.04	-0.04*	-0.02$^{\#}$	-0.05	0.03*	-0.02	0.02	0.01	0.07$^{\$}$	0.02	-0.02
Crude Oil	0.00	0.01	0.06	-0.02	-0.02	-0.03	-0.01	0.01	0.03	0.01	-0.02$^{\$}$	0.01	-0.01	-0.01	-0.01	0.01
Natural Gas	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--

*, #, $ significant at 1, 5 and 10% level respectively

Table 7 (b) VAR Model with Close-To-Open Return Volatility, Volume and Open Interest

								Volatility								
	a_1	$b_{1,1}$	$b_{1,2}$	$b_{1,3}$	$b_{1,4}$	$b_{1,5}$	$c_{1,1}$	$c_{1,2}$	$c_{1,3}$	$c_{1,4}$	$c_{1,5}$	$d_{1,1}$	$d_{1,2}$	$d_{1,3}$	$d_{1,4}$	$d_{1,5}$
Soy Bean	0.04^{*}	0.93^{*}	0.08	0.06	-0.07	-0.01	0.02	0.02	0.00	0.01	0.00	-0.05	$-0.09^{\#}$	0.07	0.03	-0.01
Maize	0.16^{*}	1.11^{*}	-0.20^{*}	0.06	-0.07	$0.08^{\#}$	0.00	$0.02^{\$}$	0.04^{*}	0.03^{*}	$0.03^{\#}$	0.03	-0.04	0.03	0.03	-0.03
Castor Seed	0.18^{*}	0.96^{*}	-0.15^{*}	0.06	-0.01	0.02	0.02	0.03^{*}	0.01	$0.02^{\$}$	-0.01	-0.01	0.00	-0.05	0.01	-0.03
Guar Seed	0.24^{*}	0.91^{*}	0.01	0.05	0.01	-0.04	0.18^{*}	$0.12^{\#}$	0.00	0.09	0.01	-0.12	-0.19	-0.16	-0.06	-0.13
Gold	0.10	0.94^{*}	0.13^{*}	-0.21^{*}	0.03	$0.06^{\#}$	0.05	-0.03	0.00	0.01	-0.02	-0.11	0.05	-0.04	-0.04	0.07
Silver	0.56	0.95^{*}	$-0.09^{\#}$	0.29^{*}	-0.27^{*}	0.03	0.27	-0.29	$0.41^{\#}$	-0.22	-0.09	0.12	0.03	-0.35	0.20	0.02
Aluminium	$0.08^{\#}$	1.04^{*}	-0.05	-0.05	-0.02	0.04	0.00	$-0.04^{\#}$	-0.01	0.02	-0.01	-0.22	-0.01	-0.04	-0.01	0.21
Copper	$0.11^{\#}$	1.00^{*}	-0.02	-0.01	-0.01	0.01	0.00	$-0.10^{\#}$	-0.07	-0.06	0.03	-0.53	-0.08	0.09	0.29	0.34
Zinc	0.15^{*}	0.99^{*}	-0.05	0.01	-0.01	0.03	0.03	-0.03	-0.01	$-0.06^{\$}$	-0.01	-0.13	0.00	-0.06	0.15	0.09
Crude Oil	-0.05	0.99^{*}	$-0.09^{\$}$	0.16^{*}	-0.05	0.01	-0.01	0.00	0.01	0.01	-0.02	-0.12	0.05	-0.05	-0.05	-0.04
Natural Gas	$0.21^{\#}$	$0.98^{\#}$	0.01	-0.03	-0.06	0.07	0.02	0.00	0.02	0.00	$0.08^{\$}$	-0.08	-0.43^{*}	0.01	-0.03	0.18
								Volume								
	a_2	$b_{2,1}$	$b_{2,2}$	$b_{2,3}$	$b_{2,4}$	$b_{2,5}$	$c_{2,1}$	$c_{2,2}$	$c_{2,3}$	$c_{2,4}$	$c_{2,5}$	$d_{2,1}$	$d_{2,2}$	$d_{2,3}$	$d_{2,4}$	$d_{2,5}$
Soy Bean	0.04	$0.18^{\#}$	$-0.22^{\#}$	0.04	-0.02	-0.01	-0.12^{*}	$-0.07^{\$}$	-0.04	0.00	0.01	0.56^{*}	-0.01	$0.21^{\#}$	$0.19^{\#}$	-0.09
Maize	-0.90^{*}	$0.23^{\#}$	$-0.42^{\#}$	-0.08	0.13	0.04	-0.05	-0.01	-0.02	-0.01	0.00	0.73^{*}	0.02	0.09	0.14	0.08
Castor Seed	-0.84^{*}	0.03	0.10	-0.37^{*}	$0.29^{\#}$	$-0.19^{\$}$	-0.05	-0.02	0.06	0.04	$0.08^{\#}$	0.46^{*}	$0.19^{\#}$	-0.05	0.13	-0.27^{*}
Guar Seed	-0.01	-0.05	-0.01	0.00	$0.10^{\#}$	-0.03	-0.07	0.02	0.02	-0.01	-0.02	0.52^{*}	0.02	0.04^{*}	0.01	-0.11
Gold	-1.87^{*}	$0.06^{\$}$	-0.06	-0.02	0.02	-0.01	-0.08^{*}	0.04	0.03	0.01	$-0.16^{\#}$	0.41^{*}	0.03	0.12	$0.24^{\#}$	0.18
Silver	-2.35^{*}	0.01	$-0.01^{\$}$	$0.01^{\$}$	$-0.01^{\$}$	0.00	-0.03	0.05	-0.09^{*}	$0.07^{\#}$	-0.01	0.22	0.13	-0.02	$0.23^{\#}$	$0.19^{\$}$
Aluminium	-0.11	0.07	-0.03	-0.14	-0.06	0.10	-0.03	-0.01	-0.05	0.01	$0.07^{\$}$	0.01	-0.06	0.15	0.13	-0.15
Copper	$-0.07^{\$}$	0.08^{*}	-0.10^{*}	0.04	0.01	-0.01	-0.12^{*}	-0.03	-0.01	-0.04	-0.10^{*}	0.26	0.47^{*}	0.25	0.19	-0.09
Zinc	-0.95^{*}	0.00	-0.05	0.02	-0.06	0.10	-0.06	-0.02	0.03	0.07	0.05	-0.02	$0.37^{\$}$	$0.34^{\$}$	0.16	0.28
Crude Oil	-0.93^{*}	0.07	-0.18	0.15	-0.13	0.09	0.05	0.00	0.01	$0.09^{\#}$	-0.09^{*}	0.10	0.47^{*}	-0.12	0.22	-0.11
Natural Gas	-0.24^{*}	-0.02	0.01	0.01	-0.05	0.04	0.01	0.04	-0.09	$0.10^{\#}$	-0.07	0.16	-0.07	0.02	0.00	-0.16
								Open Interest								
	a_3	$b_{3,1}$	$b_{3,2}$	$b_{3,3}$	$b_{3,4}$	$b_{3,5}$	$c_{3,1}$	$c_{3,2}$	$c_{3,3}$	$c_{3,4}$	$c_{3,5}$	$d_{3,1}$	$d_{3,2}$	$d_{3,3}$	$d_{3,4}$	$d_{3,5}$
Soy Bean	0.00	-0.02	0.02	-0.03	0.03	0.00	0.01	0.02	0.01	0.00	0.00	-0.02	-0.02	-0.02	-0.02	-0.03
Maize	0.01	-0.02	0.03	0.00	0.02	-0.03	0.00	$0.01^{\$}$	0.00	0.01	0.00	-0.01	-0.03	-0.01	-0.02	-0.01
Castor Seed	$-0.08^{\#}$	-0.01	0.17^{*}	$-0.11^{\#}$	-0.05	0.00	-0.02	$-0.03^{\#}$	0.00	-0.01	0.00	0.05	0.03	0.01	-0.01	0.00
Guar Seed	$-0.04^{\#}$	-0.01	0.00	0.00	0.02	0.00	0.02	0.01	0.02	0.00	-0.01	-0.08	-0.07	-0.05	-0.02	0.00
Gold	0.01	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	-0.02	-0.02	0.00	-0.01	-0.02
Silver	-0.05	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	0.00	-0.01	0.00	-0.03	0.00	-0.01	0.03	0.01
Aluminium	0.01	-0.05^{*}	0.06^{*}	-0.01	-0.01	0.01	0.02^{*}	0.00	$0.01^{\#}$	0.01	0.00	0.03	-0.02	-0.04	0.01	-0.07
Copper	0.00	-0.01	0.00	0.01	-0.01	0.01	-0.01	0.01	-0.01	0.01	-0.01	0.01	-0.01	0.01	0.02	$0.08^{\#}$
Zinc	-0.01	0.00	0.01	-0.02	0.01	0.01	-0.04^{*}	$-0.02^{\#}$	0.01	0.03^{*}	-0.01	0.02	-0.05	$0.08^{\$}$	0.02	-0.01
Crude Oil	-0.01	0.00	0.00	0.04	-0.02	-0.02	-0.01	0.01	-0.01	$0.01^{\$}$	$-0.02^{\$}$	0.00	0.04	-0.01	0.00	0.02
Natural Gas	0.00	0.00	0.03	0.01	-0.05^{*}	0.01	-0.02	0.00	0.02	0.02	0.02	-0.01	-0.04	0.03	-0.08	-0.06

*, #, $ significant at 1, 5 and 10% level respectively

Table 7 (c) VAR Model with Open-To-Close Return Volatility, Volume and Open Interest

	Volatility															
	a_1	**$b_{1,1}$**	**$b_{1,2}$**	**$b_{1,3}$**	**$b_{1,4}$**	**$b_{1,5}$**	**$c_{1,1}$**	**$c_{1,2}$**	**$c_{1,3}$**	**$c_{1,4}$**	**$c_{1,5}$**	**$d_{1,1}$**	**$d_{1,2}$**	**$d_{1,3}$**	**$d_{1,4}$**	**$d_{1,5}$**
Soy Bean	0.01*	1.12*	-0.20*	0.18*	-0.12$^{\#}$	-0.04	0.00	0.01	0.00	0.01	0.00	-0.01	-0.02	-0.02	-0.01	0.00
Maize	0.03*	0.89*	-0.10$^{\#}$	0.12	-0.12$^{\#}$	0.08$^{\#}$	0.01*	0.00	0.00	0.00	-0.01$^{\#}$	-0.01	-0.02	-0.01	0.00	0.00
Castor Seed	0.02*	1.08*	-0.18*	0.01	-0.01	0.03	0.00	0.00	0.00	0.00	0.00	-0.01	-0.01	0.00	-0.01$^{\#}$	0.00
Guar Seed	0.07	0.78*	-0.01	0.03	-0.01	-0.01	0.04	0.08*	-0.03	-0.02	-0.08*	-0.10	-0.15$^{\#}$	-0.03	0.10	0.13$^{\#}$
Gold	0.01$^{\#}$	0.93*	-0.08$^{\#}$	0.05	-0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.01*	0.00	-0.01	-0.01	-0.01
Silver	0.05*	1.17*	-0.29*	0.32*	-0.40*	0.12*	0.01	0.00	0.00	0.00	0.01*	0.00	0.00	-0.01	-0.01	-0.01
Aluminium	0.02*	0.99*	-0.09	0.08	-0.09	0.06	0.00	0.01	0.00	0.00	0.01$^{\$}$	-0.11*	-0.01	-0.03	0.03	-0.02
Copper	0.00$^{\$}$	0.94*	0.00	-0.01	0.01	0.03	0.01*	0.00$^{\$}$	0.01$^{\#}$	0.00	-0.01*	-0.02	0.00	0.00	-0.02$^{\$}$	0.00
Zinc	0.03$^{\#}$	0.90*	0.03	0.18*	-0.13$^{\#}$	-0.07$^{\#}$	0.01	0.00	0.01	0.00	0.00	-0.04	-0.02	0.01	0.01	0.00
Crude Oil	0.00	0.98*	0.03	-0.05	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Natural Gas	0.02$^{\#}$	0.90*	0.15$^{\#}$	-0.02	-0.07	0.01	0.00	0.00	0.00	0.00	0.01$^{\$}$	-0.02	0.00	0.01	0.01	-0.02
	Volume															
	a_2	**$b_{2,1}$**	**$b_{2,2}$**	**$b_{2,3}$**	**$b_{2,4}$**	**$b_{2,5}$**	**$c_{2,1}$**	**$c_{2,2}$**	**$c_{2,3}$**	**$c_{2,4}$**	**$c_{2,5}$**	**$d_{2,1}$**	**$d_{2,2}$**	**$d_{2,3}$**	**$d_{2,4}$**	**$d_{2,5}$**
Soy Bean	0.02	-0.13	0.11	-0.09	0.14	-0.12	-0.10*	-0.07$^{\#}$	-0.03	0.00	0.02	0.56*	-0.03	0.20$^{\#}$	0.20$^{\#}$	-0.10
Maize	-1.14*	3.23*	-4.30*	2.99*	-1.71*	0.05	-0.03	-0.03	-0.04	0.01	0.02	0.58*	0.05	0.02	0.13	0.05
Castor Seed	-0.91*	0.24	1.33	-1.99$^{\#}$	0.45	-0.28	-0.04	0.00	0.04	0.05	0.07$^{\$}$	0.42*	0.18$^{\$}$	-0.02	0.13	-0.27*
Guar Seed	-0.05	-0.01	0.16$^{\#}$	-0.13$^{\$}$	-0.04	0.16*	-0.13*	-0.02	-0.04	-0.01	-0.01	0.61*	0.10	0.07	-0.03	-0.16
Gold	-1.90*	0.45	-0.07	-0.54	-0.06	0.17	-0.06	0.05	0.02	0.01	-0.17*	0.42*	0.02	0.14	0.26$^{\#}$	0.12
Silver	-2.49*	-0.13	-0.10	-0.58	0.57	-0.17	-0.02	0.05	-0.09*	0.07$^{\#}$	-0.08*	0.22	0.13	-0.02	0.25$^{\#}$	0.21$^{\#}$
Aluminium	-0.27*	-0.41	0.32	-0.19	-0.01	0.09	-0.06	-0.02	-0.10*	-0.01	-0.06	0.08	0.37	-0.09	0.27	-0.25
Copper	-0.02	-0.95$^{\#}$	1.26$^{\#}$	-0.21	0.14	-0.07	-0.09*	-0.02	0.00	-0.02	-0.09*	0.28	0.37$^{\#}$	0.24	0.15	-0.12
Zinc	-0.99*	-0.34	0.50	0.05	-0.75	0.64$^{\#}$	-0.07	-0.03	0.01	0.04	0.07	-0.01	0.34$^{\$}$	0.36$^{\$}$	0.16	0.31
Crude Oil	-1.01$^{\#}$	-1.63	0.11	1.99	-2.83	2.60	0.05	-0.01	0.01	0.08$^{\#}$	-0.10*	0.11	0.45$^{\#}$	-0.11	0.19	-0.11
Natural Gas	-0.29*	0.55	-0.82	0.65	-0.77	0.39	0.02	0.04	-0.09$^{\#}$	0.08$^{\$}$	-0.07	0.13	-0.08	0.03	-0.02	-0.16
	Open Interest															
	a_3	**$b_{3,1}$**	**$b_{3,2}$**	**$b_{3,3}$**	**$b_{3,4}$**	**$b_{3,5}$**	**$c_{3,1}$**	**$c_{3,2}$**	**$c_{3,3}$**	**$c_{3,4}$**	**$c_{3,5}$**	**$d_{3,1}$**	**$d_{3,2}$**	**$d_{3,3}$**	**$d_{3,4}$**	**$d_{3,5}$**
Soy Bean	0.00	0.09	-0.18	0.07	-0.11	0.12	0.00	0.02	0.00	0.00	0.00	-0.02	-0.02	-0.02	-0.01	-0.03
Maize	-0.01	0.03	0.01	0.12	-0.04	-0.07	0.00	0.01	0.00	0.00	0.00	-0.01	-0.02	0.00	-0.01	0.00
Castor Seed	-0.04	0.18	0.65$^{\#}$	-0.83*	0.12	-0.06	-0.02	-0.01	0.00	0.00	0.00	0.04	0.01	0.00	0.00	0.00
Guar Seed	-0.03*	-0.02	0.18*	-0.10*	0.00	0.02	-0.01	0.01	0.00	-0.01	-0.01	-0.04	-0.07$^{\$}$	-0.03	-0.01	0.00
Gold	0.00	0.17	-0.15	-0.02	-0.04	0.05	0.00	0.00	0.00	-0.01	0.01	-0.01	-0.02	0.01	-0.01	0.01
Silver	-0.04	-0.11	0.04	-0.11	0.22	-0.07	-0.01	0.00	0.00	-0.01	0.00	-0.03	0.00	-0.01	0.04	0.01
Aluminium	0.01	-0.01	-0.02	0.02	-0.05	0.05	0.01	0.00	0.01$^{\#}$	0.01	0.00	0.04	-0.01	-0.04	0.02	-0.07$^{\$}$
Copper	0.00	-0.03	-0.08	0.15	-0.14	0.12	-0.01	0.01	-0.01	0.01	0.00	0.01	0.00	0.01	0.02	0.08$^{\#}$
Zinc	-0.03	-0.01	0.04	-0.05	-0.04	0.04	-0.04*	-0.02$^{\#}$	0.00	0.03*	-0.01	0.02	-0.05	0.07	0.01	-0.01
Crude Oil	0.00	-0.34	0.89	-0.63	-0.17	0.20	-0.01	0.01	-0.01	0.01$^{\$}$	-0.02	0.02	0.03	0.00	-0.01	0.01
Natural Gas	0.05$^{\#}$	-0.03	0.12	-0.03	0.08	-0.20	-0.02	0.01	0.03$^{\#}$	0.02	0.02$^{\$}$	-0.01	-0.05	0.03	-0.10$^{\#}$	-0.08$^{\$}$

*, #, $ significant at 1, 5 and 10% level respectively

Table 8 (a): Variance Decomposition: When Volatility is the Dependent Variable

A. Volatility Explained By Volatility

	Close-to-close Volatility					Close-to-open Volatility					Open-to-close Volatility				
Lag->	1	5	10	15	20	1	5	10	15	20	1	5	10	15	20
Soy Bean	100%	92%	91%	91%	90%	100%	100%	99%	99%	99%	100%	99%	99%	99%	99%
Maize	100%	85%	83%	82%	81%	100%	98%	93%	92%	92%	100%	99%	99%	99%	99%
Castor Seed						100%	98%	98%	97%	97%	100%	99%	96%	96%	96%
Guar Seed	100%	62%	55%	54%	53%	100%	97%	97%	96%	96%	100%	99%	98%	98%	98%
Gold	100%	96%	96%	96%	96%	100%	100%	100%	100%	100%	100%	100%	99%	99%	99%
Silver	100%	97%	97%	97%	97%	100%	100%	100%	100%	100%	100%	99%	97%	97%	96%
Aluminium	100%	88%	88%	88%	88%	100%	99%	99%	99%	99%	100%	98%	98%	98%	98%
Copper	100%	95%	97%	97%	97%	100%	99%	99%	99%	99%	100%	96%	96%	96%	96%
Zinc	100%	89%	90%	90%	90%	100%	99%	98%	97%	97%	100%	99%	98%	98%	98%
Crude Oil	100%	95%	95%	95%	95%	100%	99%	99%	99%	98%	100%	100%	100%	100%	100%
Natural Gas						100%	99%	99%	98%	98%	100%	100%	100%	100%	100%

B. Volatility Explained By Volume

	Close-to-close Volatility					Close-to-open Volatility					Open-to-close Volatility				
Lag->	1	5	10	15	20	1	5	10	15	20	1	5	10	15	20
Soy Bean	0%	7%	8%	9%	9%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Maize	0%	15%	17%	18%	18%	0%	2%	7%	8%	8%	0%	1%	1%	1%	1%
Castor Seed						0%	2%	2%	2%	3%	0%	0%	0%	0%	0%
Guar Seed	0%	24%	29%	30%	30%	0%	2%	3%	3%	3%	0%	1%	1%	1%	1%
Gold	0%	4%	4%	4%	4%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Silver	0%	3%	3%	3%	3%	0%	0%	0%	0%	0%	0%	1%	3%	3%	3%
Aluminium	0%	9%	8%	8%	8%	0%	1%	1%	1%	1%	0%	0%	0%	0%	0%
Copper	0%	5%	3%	3%	2%	0%	1%	1%	1%	1%	0%	4%	3%	3%	3%
Zinc	0%	10%	10%	10%	10%	0%	0%	0%	1%	1%	0%	1%	1%	1%	1%
Crude Oil	0%	5%	5%	5%	5%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Natural Gas						0%	0%	0%	1%	1%	0%	0%	0%	0%	0%

C. Volatility Explained By Open Interest

	Close-to-close Volatility					Close-to-open Volatility					Open-to-close Volatility				
Lag->	1	5	10	15	20	1	5	10	15	20	1	5	10	15	20
Soy Bean	0%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	1%	1%	1%	1%
Maize	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Castor Seed						0%	0%	0%	0%	0%	0%	1%	3%	4%	4%
Guar Seed	0%	14%	16%	16%	17%	0%	0%	1%	1%	1%	0%	1%	1%	1%	1%
Gold	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	1%	1%	1%
Silver	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Aluminium	0%	2%	4%	4%	4%	0%	0%	0%	0%	0%	0%	2%	2%	2%	2%
Copper	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	1%	1%	1%
Zinc	0%	0%	0%	0%	0%	0%	1%	2%	2%	2%	0%	0%	0%	0%	0%
Crude Oil	0%	0%	0%	0%	0%	0%	1%	1%	1%	2%	0%	0%	0%	0%	0%
Natural Gas						0%	1%	1%	1%	1%	0%	0%	0%	0%	0%

Table 8 (b): Variance Decomposition: When Volume is the Dependent Variable

	Close-to-close Volatility					Close-to-open Volatility					Open-to-close Volatility				
A. Volume Explained By Volatility															
	1	5	10	15	20	1	5	10	15	20	1	5	10	15	20
Soy Bean	0%	1%	1%	1%	1%	8%	9%	9%	9%	9%	0%	0%	0%	0%	0%
Maize	7%	7%	8%	8%	8%	3%	5%	5%	5%	5%	5%	13%	13%	13%	13%
Castor Seed						8%	9%	9%	9%	9%	0%	1%	1%	1%	1%
Guar Seed	0%	1%	2%	2%	2%	14%	16%	16%	16%	16%	0%	1%	2%	2%	2%
Gold	0%	0%	1%	1%	1%	5%	5%	5%	5%	5%	0%	0%	0%	0%	0%
Silver	0%	1%	2%	2%	2%	2%	3%	4%	4%	5%	0%	1%	1%	1%	1%
Aluminium	0%	1%	1%	1%	2%	8%	9%	10%	10%	10%	0%	1%	1%	1%	1%
Copper	1%	2%	2%	2%	2%	5%	6%	6%	6%	6%	0%	1%	1%	1%	1%
Zinc	0%	1%	1%	1%	1%	10%	10%	10%	10%	10%	0%	1%	1%	1%	1%
Crude Oil	0%	0%	0%	0%	0%	6%	6%	6%	6%	6%	0%	0%	0%	0%	0%
Natural Gas						9%	9%	9%	9%	9%	0%	1%	1%	1%	1%
B. Volume Explained By Volume															
	Close-to-close Volatility					Close-to-open Volatility					Open-to-close Volatility				
	1	5	10	15	20	1	5	10	15	20	1	5	10	15	20
Soy Bean	100%	95%	95%	95%	95%	92%	87%	87%	87%	87%	100%	96%	95%	95%	95%
Maize	93%	91%	91%	91%	91%	97%	94%	94%	93%	93%	95%	86%	86%	86%	86%
Castor Seed						92%	88%	87%	87%	87%	100%	96%	95%	95%	95%
Guar Seed	100%	95%	95%	95%	95%	86%	82%	82%	82%	82%	100%	96%	94%	94%	94%
Gold	100%	98%	98%	98%	98%	95%	93%	93%	93%	93%	100%	98%	98%	98%	98%
Silver	100%	98%	97%	97%	97%	98%	96%	95%	94%	94%	100%	98%	97%	97%	97%
Aluminium	100%	98%	98%	98%	98%	92%	90%	90%	90%	90%	100%	99%	99%	99%	99%
Copper	99%	97%	97%	97%	97%	95%	93%	92%	92%	92%	100%	98%	98%	98%	98%
Zinc	100%	98%	98%	98%	98%	90%	89%	88%	88%	88%	100%	98%	97%	97%	97%
Crude Oil	100%	98%	98%	98%	98%	94%	93%	93%	93%	93%	100%	98%	98%	98%	98%
Natural Gas						91%	90%	90%	90%	90%	100%	98%	98%	98%	98%
C. Volume Explained By Open Interest															
	Close-to-close Volatility					Close-to-open Volatility					Open-to-close Volatility				
	1	5	10	15	20	1	5	10	15	20	1	5	10	15	20
Soy Bean	0%	4%	4%	4%	4%	0%	4%	4%	4%	4%	0%	4%	4%	4%	4%
Maize	0%	1%	1%	1%	1%	0%	1%	1%	1%	1%	0%	1%	1%	1%	1%
Castor Seed						0%	3%	4%	4%	4%	0%	3%	3%	3%	3%
Guar Seed	0%	3%	3%	4%	4%	0%	2%	2%	2%	2%	0%	3%	3%	3%	3%
Gold	0%	2%	2%	2%	2%	0%	2%	2%	2%	2%	0%	2%	2%	2%	2%
Silver	0%	1%	1%	1%	1%	0%	1%	1%	1%	1%	0%	1%	1%	1%	1%
Aluminium	0%	1%	1%	1%	1%	0%	0%	0%	0%	0%	0%	1%	1%	1%	1%
Copper	0%	1%	1%	1%	1%	0%	1%	1%	1%	1%	0%	1%	1%	1%	1%
Zinc	0%	1%	2%	2%	2%	0%	1%	2%	2%	2%	0%	1%	2%	2%	2%
Crude Oil	0%	2%	2%	2%	2%	0%	2%	2%	2%	2%	0%	2%	2%	2%	2%
Natural Gas						0%	0%	0%	0%	0%	0%	0%	0%	0%	0%

Table 8 (c): Variance Decomposition: When Open Interest is the Dependent Variable

A. Open Interest Explained By Volatility

	Close-to-close Volatility					Close-to-open Volatility					Open-to-close Volatility				
	1	5	10	15	20	1	5	10	15	20	1	5	10	15	20
Soy Bean	0%	0%	0%	0%	0%	1%	1%	1%	1%	1%	0%	1%	1%	1%	1%
Maize	0%	2%	2%	2%	2%	0%	1%	1%	1%	1%	1%	2%	2%	2%	2%
Castor Seed						0%	2%	2%	2%	2%	0%	2%	2%	2%	2%
Guar Seed	0%	1%	1%	1%	1%	1%	1%	1%	1%	2%	0%	7%	8%	8%	8%
Gold	0%	1%	1%	1%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Silver	0%	1%	1%	1%	1%	0%	1%	1%	1%	1%	0%	0%	0%	0%	0%
Aluminium	0%	1%	1%	1%	1%	0%	2%	2%	2%	2%	0%	0%	0%	0%	0%
Copper	0%	1%	1%	1%	1%	0%	1%	1%	1%	1%	0%	0%	0%	0%	0%
Zinc	0%	1%	1%	1%	1%	3%	4%	4%	4%	4%	0%	0%	0%	0%	0%
Crude Oil	0%	1%	1%	1%	1%	1%	1%	1%	1%	1%	0%	0%	0%	0%	0%
Natural Gas						1%	5%	5%	5%	5%	0%	1%	1%	1%	1%

B. Open Interest Explained By Volume

	Close-to-close Volatility					Close-to-open Volatility					Open-to-close Volatility				
	1	5	10	15	20	1	5	10	15	20	1	5	10	15	20
Soy Bean	12%	12%	12%	12%	12%	11%	11%	11%	11%	11%	12%	12%	12%	12%	12%
Maize	2%	2%	2%	2%	2%	2%	2%	2%	2%	2%	1%	1%	1%	1%	1%
Castor Seed						8%	8%	8%	8%	8%	6%	6%	6%	6%	6%
Guar Seed	29%	29%	29%	29%	29%	38%	38%	38%	38%	38%	29%	27%	27%	27%	27%
Gold	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%
Silver	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%	3%
Aluminium	2%	4%	4%	4%	4%	3%	6%	6%	6%	6%	2%	4%	4%	4%	4%
Copper	2%	3%	3%	3%	3%	2%	2%	2%	2%	2%	2%	3%	3%	3%	3%
Zinc	0%	5%	6%	6%	6%	0%	5%	5%	5%	5%	0%	5%	5%	5%	5%
Crude Oil	0%	1%	1%	1%	1%	0%	1%	1%	1%	1%	0%	1%	1%	1%	1%
Natural Gas						2%	3%	4%	4%	4%	3%	5%	5%	5%	5%

C. Open Interest Explained By Open Interest

	Close-to-close Volatility					Close-to-open Volatility					Open-to-close Volatility				
	1	5	10	15	20	1	5	10	15	20	1	5	10	15	20
Soy Bean	88%	88%	88%	88%	88%	88%	88%	88%	88%	88%	88%	88%	87%	87%	87%
Maize	98%	96%	95%	95%	95%	98%	96%	96%	96%	96%	98%	97%	97%	97%	97%
Castor Seed						92%	90%	90%	90%	90%	94%	92%	92%	92%	92%
Guar Seed	71%	70%	70%	70%	70%	61%	61%	61%	61%	61%	71%	66%	65%	65%	65%
Gold	97%	96%	96%	96%	96%	97%	97%	97%	97%	97%	97%	97%	97%	97%	97%
Silver	97%	96%	96%	96%	96%	97%	96%	96%	96%	96%	97%	97%	97%	96%	96%
Aluminium	97%	95%	94%	94%	94%	97%	93%	93%	93%	93%	98%	96%	96%	96%	96%
Copper	98%	96%	96%	96%	96%	98%	96%	96%	96%	96%	98%	97%	97%	97%	97%
Zinc	100%	94%	94%	94%	94%	97%	92%	91%	91%	91%	100%	95%	95%	94%	94%
Crude Oil	100%	98%	98%	98%	98%	99%	98%	98%	98%	98%	100%	99%	99%	99%	98%
Natural Gas						96%	92%	92%	92%	92%	97%	95%	94%	94%	94%

We find that volatility is mostly explained by its own lagged volatilities in all cases expect for agricultural commodities and that too when close-to-close volatility is considered as a dependent variable. In case of close-to-close volatility, volume explains more than 5% of its variation [e.g. Soybean 9%, Maize 18%, Guar seed 30%, Gold 4%, silver 3%, Aluminum 8%, Copper 3%, and Crude 5%). When trading and non-trading volatilities are considered, the percentage of variation in volatility explained by unexpected volume is around 1-2% only. Similar results are found in next to near month futures (given in the Appendix). The open interest has very less explanatory power in explaining volatility except in case of Guar seed (explains 16% of variation) and Aluminum (4%) when close-to-close return volatility is taken as dependent variable. In all other cases and commodities the unexpected open interest has a minor effect (1%). These results support the findings of Granger causality and VAR results.

When unexpected volume is considered as a dependent variable, the relative impact of its own lags, volatility and the unexpected open interest is give in Table 8 (b). It is found that the lagged volume explains most of the portion of its variation. However, we find sizable effect of volatility in explaining variation in the unexpected volume. This effect is more prominent in case of non-agricultural commodities and when over night volatility measured by close-to-open return volatility is considered. In case of Maize, all three measures of volatility explain around 7% of variation in the volume. However, non-trading volatility explains around 9% in Soybean, 8% in Castor, 5% in Gold, 4% in Silver, 10% in Aluminium, 5% in Copper, 10% in Zinc, 6% in Crude oil and, 9% in Natural gas. The effect of the unexpected open interest in explaining volume is minimal and around 3% of variation is explained in case of agricultural commodities. In non-agricultural commodities, it is around (1%). We find similar results for next to near month contracts (results are given in the Appendix). These results are also consistent with the Granger causality and VAR results.

Table 8 (c) represents the percentage of variation of the open interest explained by its own lag, volatility and the unexpected volume. All three measures of volatility also account for small variations in unexpected open interest for all commodities in both near and next to near month futures contracts. It typically explains 0 to 5% of the variation in unexpected open interest with highest explanatory power of 5% for Natural gas when non-trading volatility is considered. In case of agricultural commodities the unexpected volume explains a meaningful portion of variation (e.g. Soybean (12%), Maize (2%), Castor seed (8%), and Guar seed (30%)) in near month futures contracts. In next to near month contracts, it explains 0-10% of the variation in unexpected open interest with the highest explanatory power of 10% for Guar seed. In case of non-agricultural commodities, the unexpected volume explains around 2-5% of the variation in the unexpected open interest in near month futures contracts. However, the explanatory power of the unexpected volume tremendously increases in next to near month futures. In case of Gold and Silver, it explains around 30% of variation, Aluminium 20%, Copper 45%, Zinc 50% Crude 65%, and Natural gas 40%, of the variation in the unexpected open interest.

To conclude, the forecast error variance decomposition results between unexpected trading activity including unexpected volume and unexpected open interest and futures price volatility suggest that trading and non-trading volatility are not explained by lagged unexpected volume or lagged unexpected open interest. However, some variation (5-10%) in daily volatility measured by close-to-close returns are explained by lagged volatility. The unexpected open interest has no explanatory power in explaining futures volatility. These results are consistent with our results on MDH and Granger causality. It is important to note that only lagged non-trading volatility is able to explain the volatility (5-15%) in most of the commodities among all three measures of volatility. Another important observation from our analysis is that the open interest is not able to explain more than (0-1%) variation in volume, however, lagged volume is able to explain more than 30% variation in open interest in next to near month futures mostly for non-agricultural commodities. We also perform impulse response function on forecast error of endogenous variable in VAR system.

3.2.3 Impulse Response Analysis

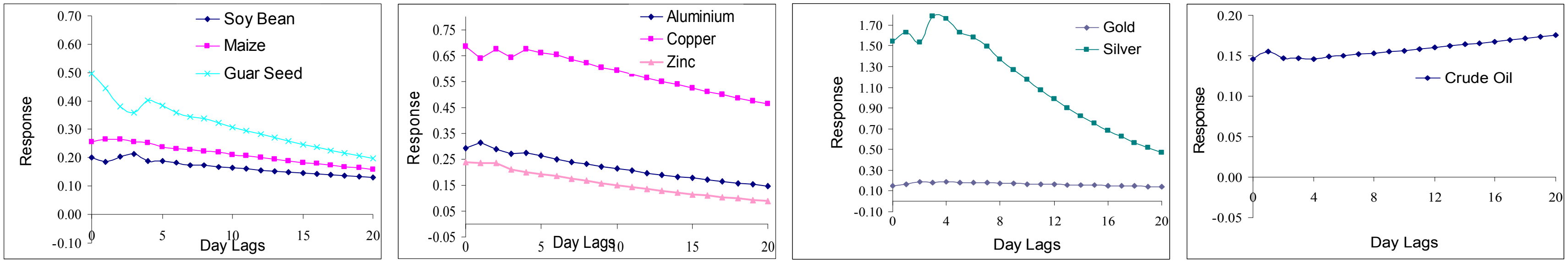
One of the well established methods of VAR analysis is the impulse-response function, which simulates the effects of a shock to one variable in the system on the conditional forecast of another variable. It explains the impact of an exogenous shock in one variable on the other variables of the system. We use the impulse-response function to analyze the impact of change in one variable (say volatility) on other variables (volume or open interest). There measures of volatility- close-to-close, close-to-open and open-to-close volatility, are used to analyze the dynamic relationship.

Figure 1-3 explain the behavior of volatility response to shock in a) volatility, b) volume and c) open interest shock. In Figure 1; close-to-close volatility, in figure 2; close-to-open volatility and Figure 3; open to close volatility are considered. In case of agricultural commodities, speed of adjustment to its own volatility shock is high and it stabilizes after 15 days with highest speed in guar seed. This adjustment is also fast in trading volatility as compared to non-trading volatility. In case of non-agricultural commodities also, volatility shock shows more persistence with highest persistence in case of Crude and Silver. Trading volatility shock adjustment is small and fast in case of non-agricultural commodities as compared to agricultural commodities. It is very interesting to see that response of volatility to volume shock across three measures of volatility. The volatility response to volume shock does not stabilize after 10 days. The non-trading volume response to volume shock is positive for all agricultural commodities, Gold, Silver and Natural gas. However, metals and Crude oil volume shock produces negative response in return volatility. In case of trading volume, its response to volume shock is positive for all commodities except Guar seed and Natural gas where alternate negative and positive response is found. In Indian commodity market, we find that for agricultural commodities there is positive volatility-volume relationship which supports the findings of Bessembinder and Seguin (1993). A negative relationship is found between futures volatility and volume in case of industrial metals and Crude which is consistent with the findings in Conard (1994). The response of volatility to open interest shock is mostly negative across all volatility measures except for Maize and Natural gas. In case of Gold and Crude, the response is minimal.

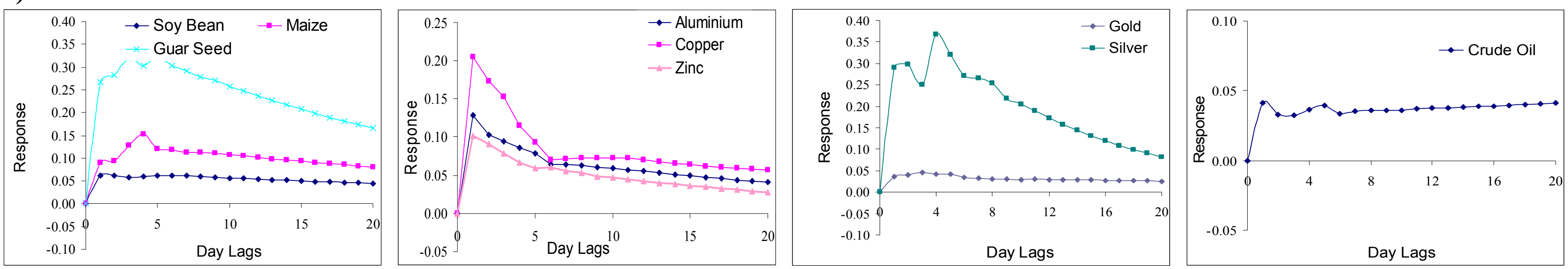
The response of trading volume to shocks in volatility, lagged volume and open interest is presented in Figure 4-6. Interestingly, volatility shock in most of the commodities produces both positive and negative adjustment in trading volume. In case of non-trading volatility, the volatility shock to volume stabilizes after 5 days and for trading volatility; it stabilizes earlier (2 days).

Figure 1: Impulse Response Function for Commodity Futures Close-To-Close Volatility Response to Shock in a) Volatility, b) Volume and c) Open Interest Shock

a) Volatility



b) Volume



c) Open Interest

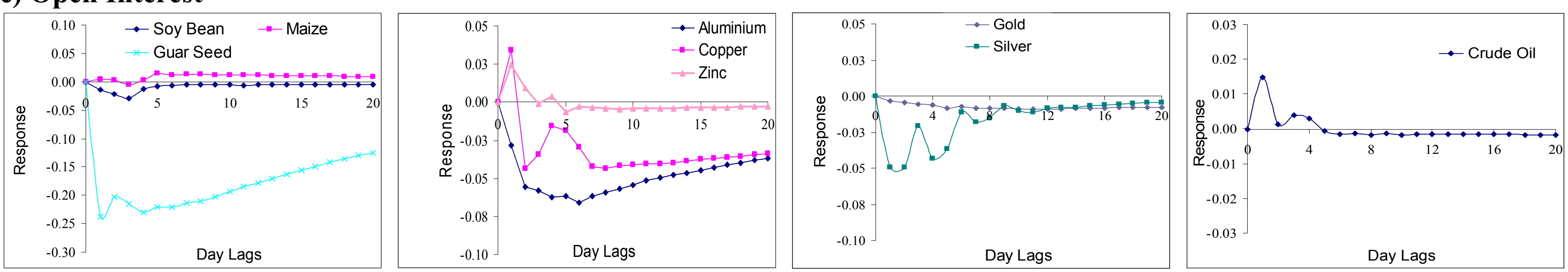
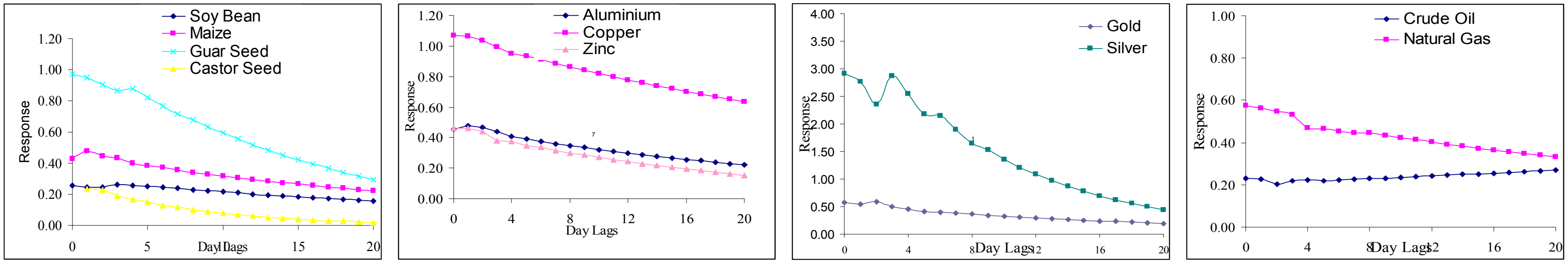
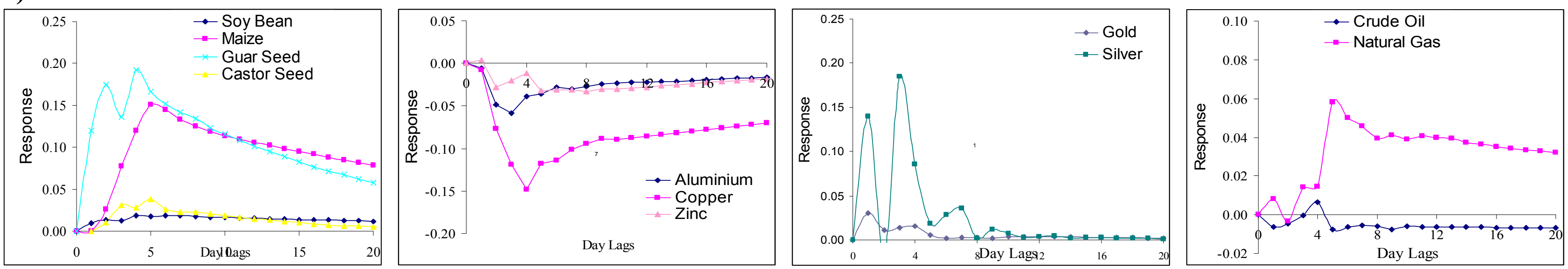


Figure 2 Impulse Response Function for Commodity Futures Close-To-Open Volatility Response to Shock in a) Volatility, b) Volume and c) Open Interest Shock

a) Volatility



b) Volume



c) Open Interest

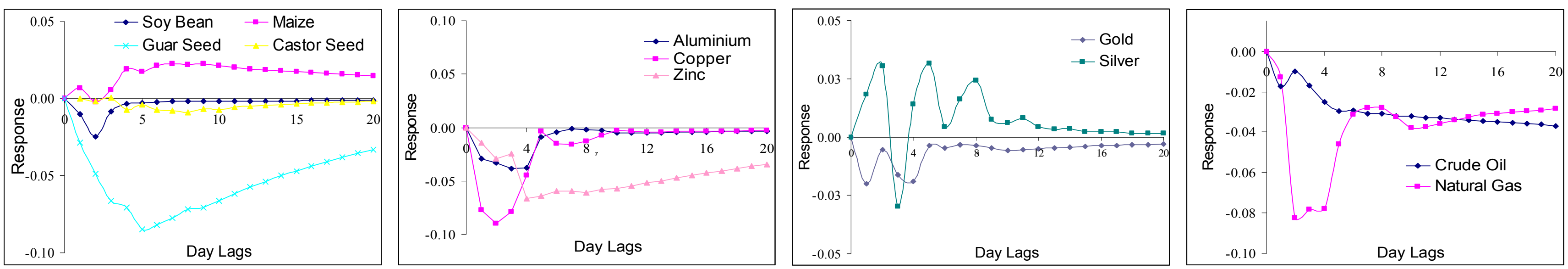
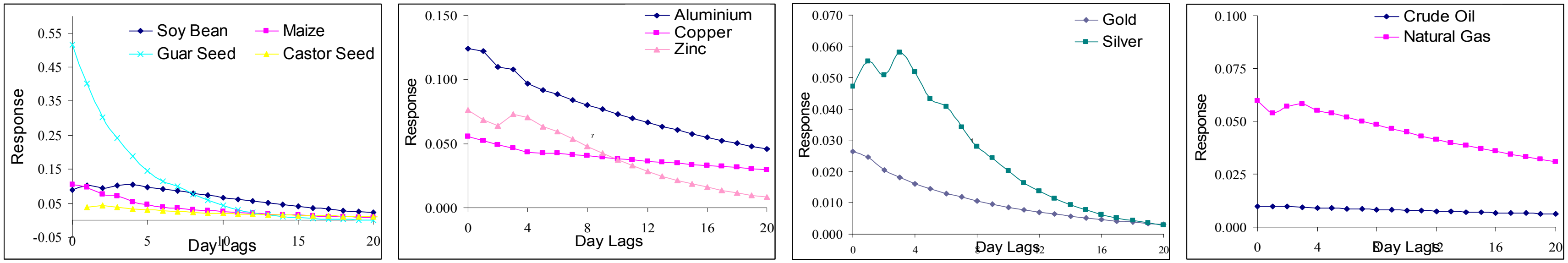
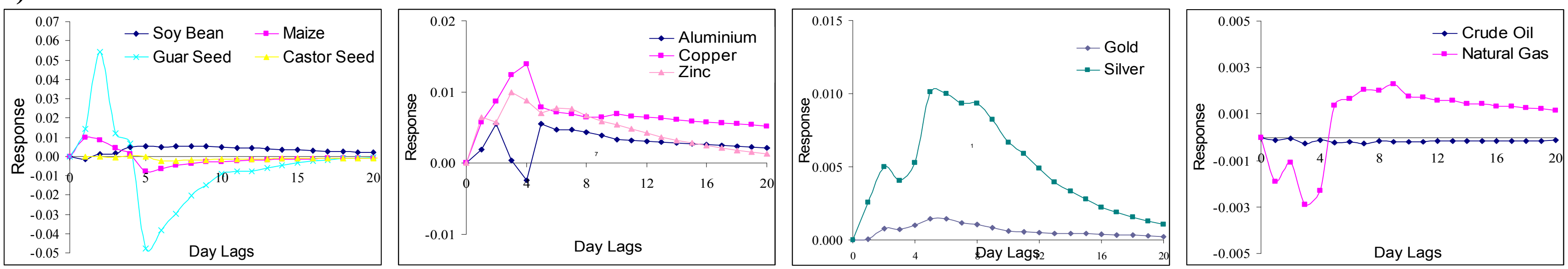


Figure 3: Impulse Response Function for Commodity Futures Open-To-Close Volatility Response to Shock in a) Volatility, b) Volume and c) Open Interest Shock

a) Volatility



b) Volume



c) Open Interest

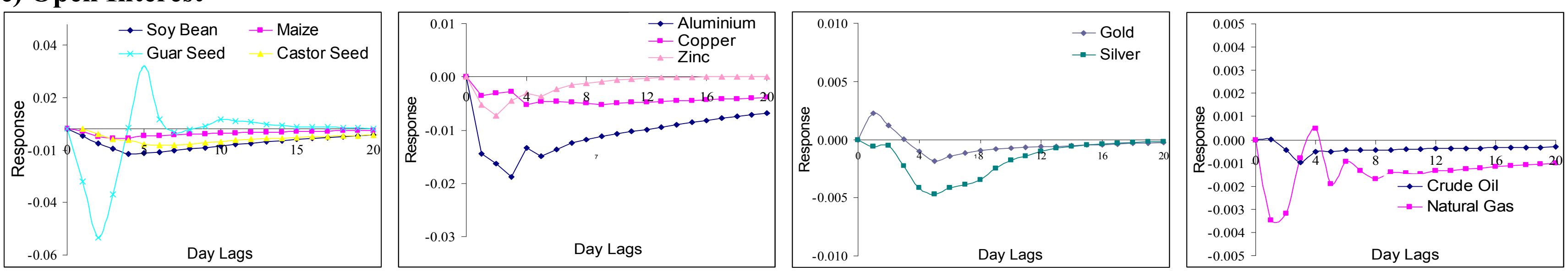
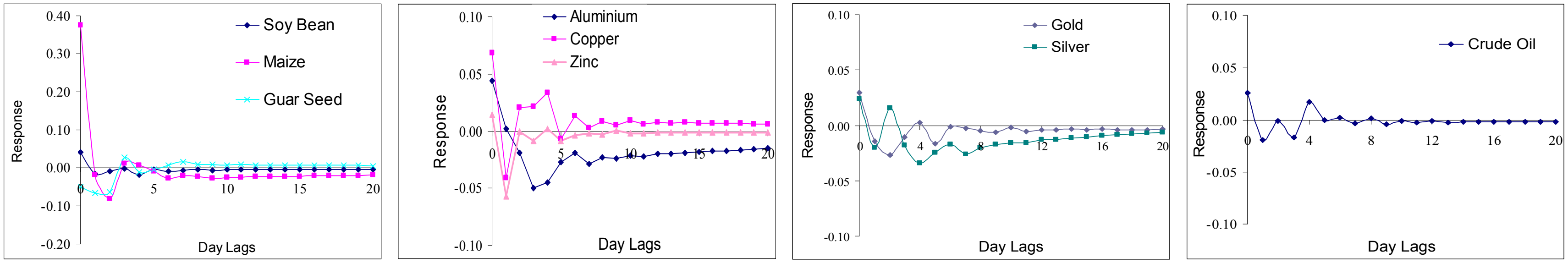
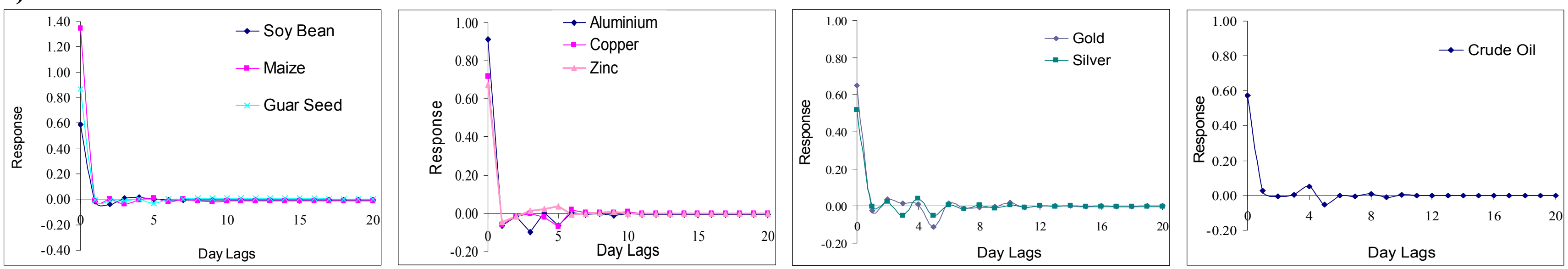


Figure 4: Impulse Response Function for Commodity Futures Volume Response to Shock in a) To Close-To-Close Volatility, b) Volume and c) Open Interest Shock

a) Volatility



b) Volume



c) Open interest

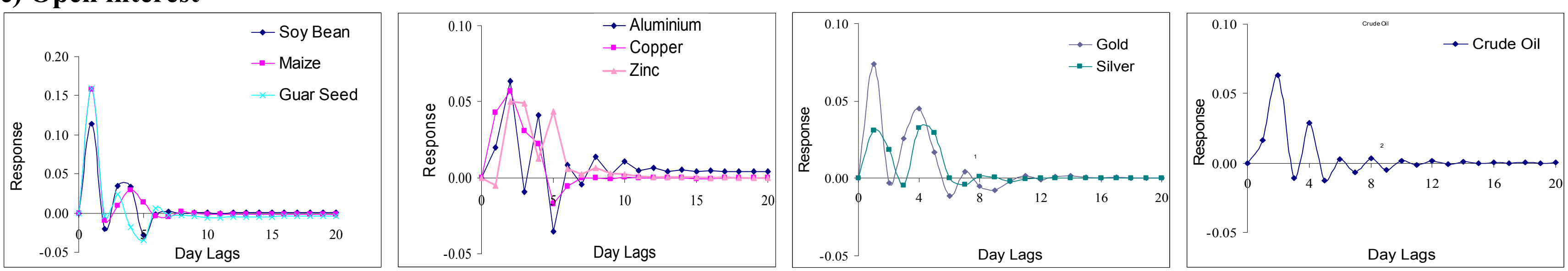


Figure 5: Impulse Response Function for Commodity Futures Volume Response to Shock in A) To Close-To-Open Volatility, b) Volume and c) Open Interest Shock

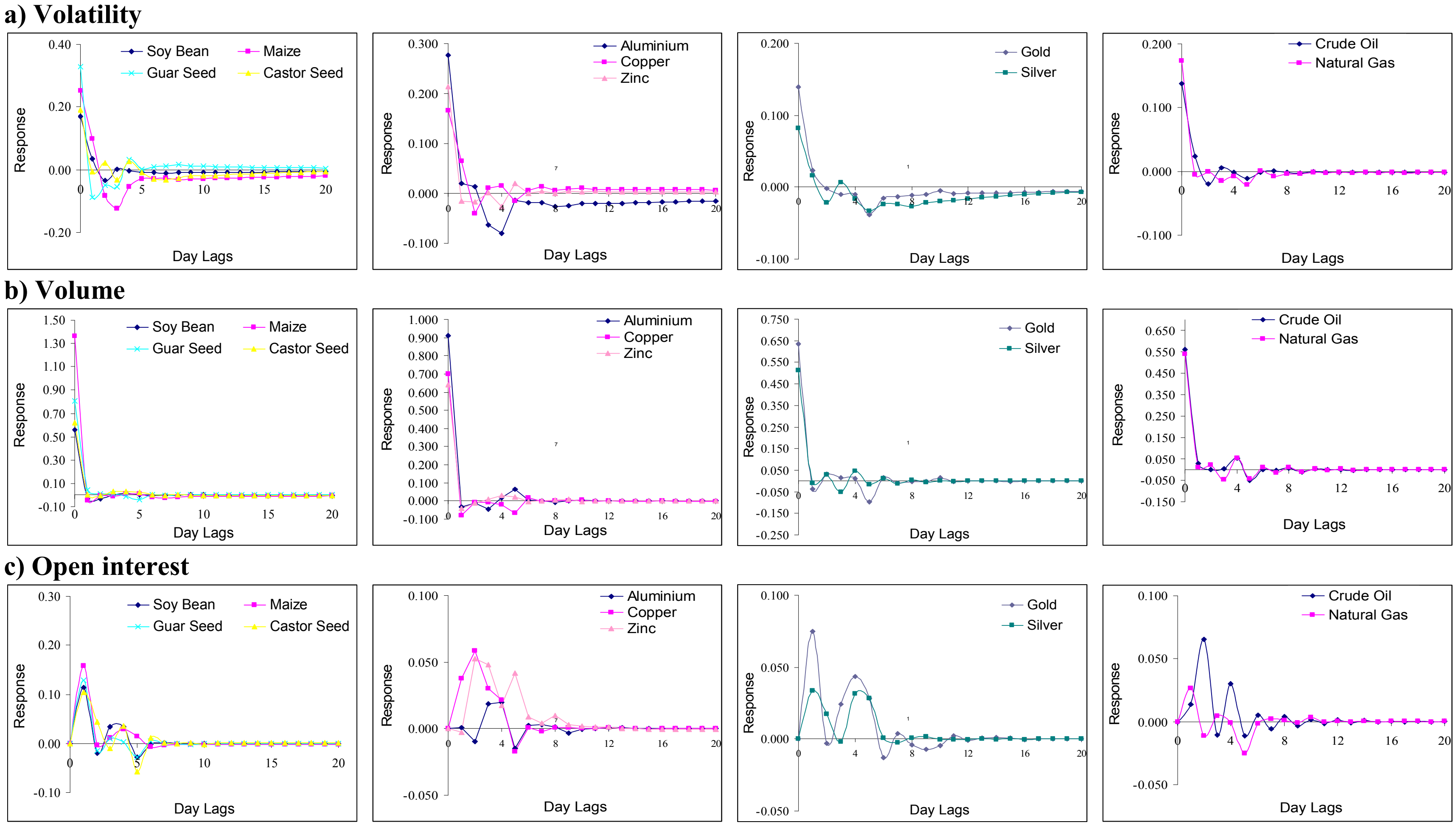
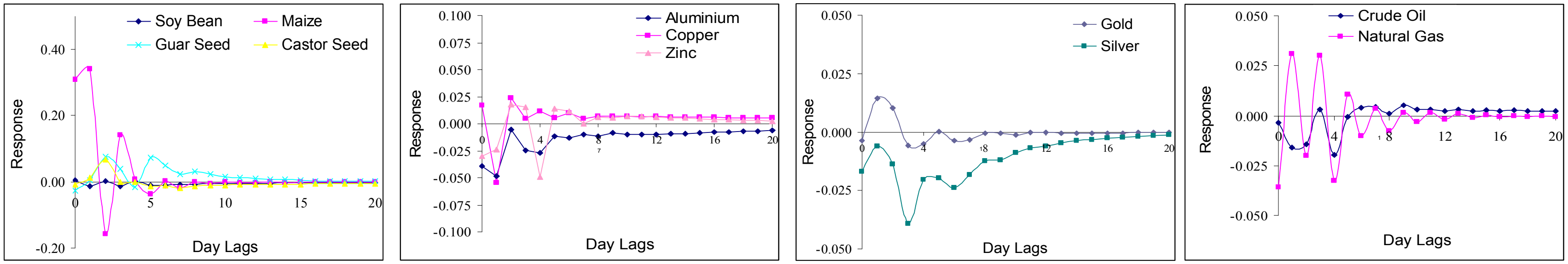
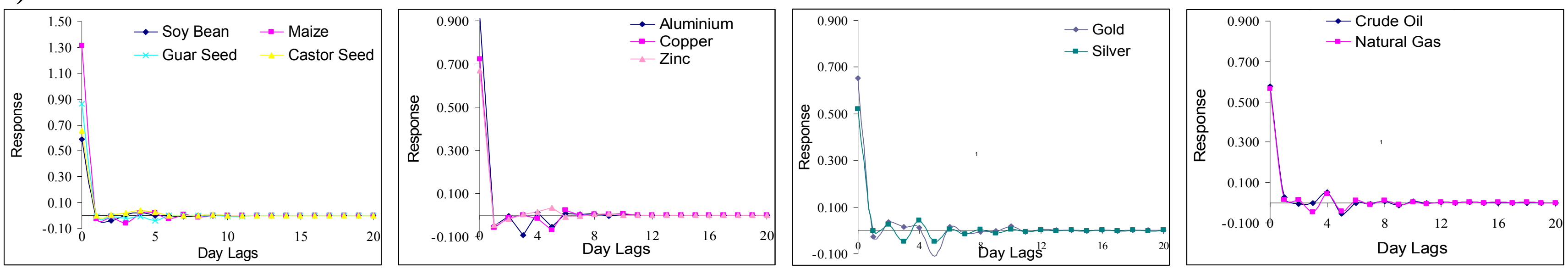


Figure 6: Impulse Response Function for Commodity Futures Volume Response to Shock in a) To Open-To-Close Volatility, b) Volume and c) Open Interest Shock

a) Volatility



b) Volume



c) Open interest

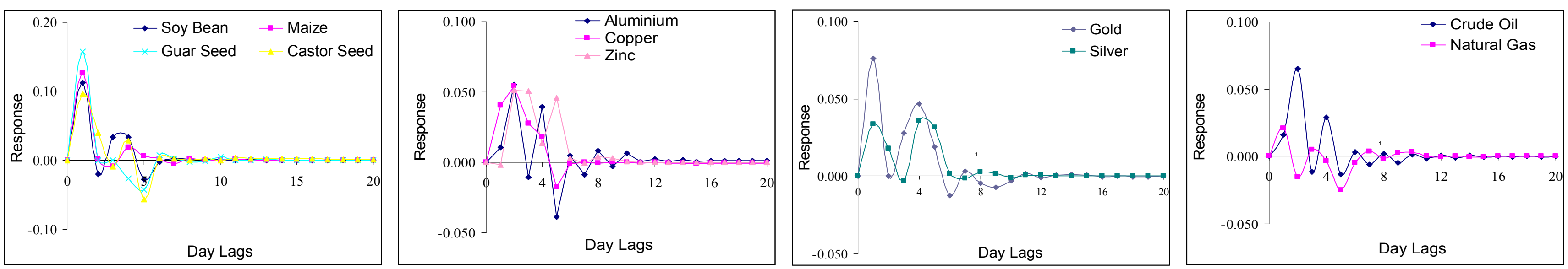
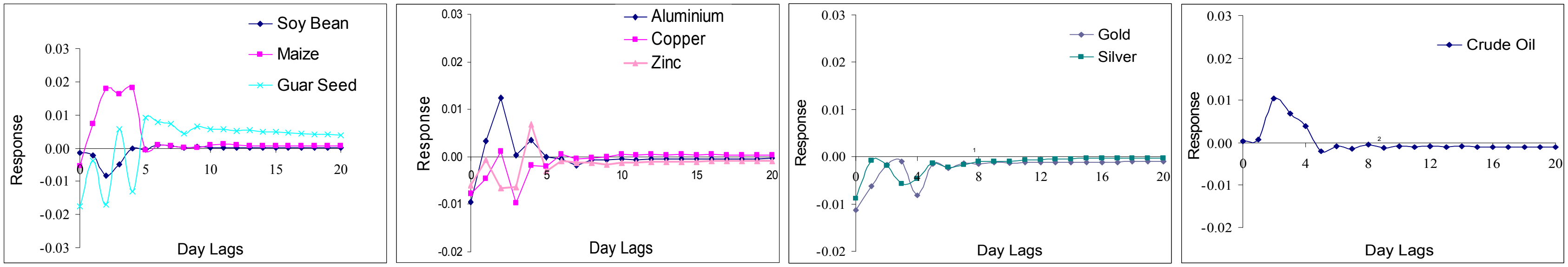
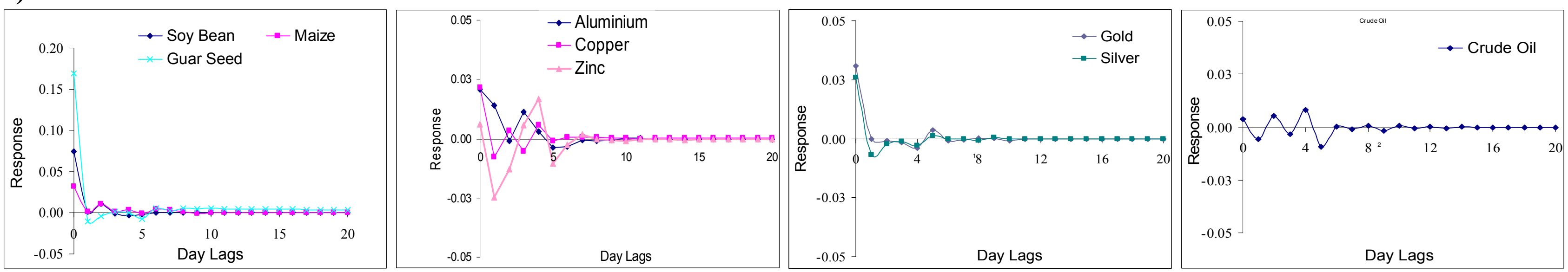


Figure 7: Impulse Response Function for Commodity Futures Open Interest Response to Shock in a) To Close-To-Close Volatility, b) Volume and c) Open Interest Shock

a) Volatility



b) Volume



c) Open interest

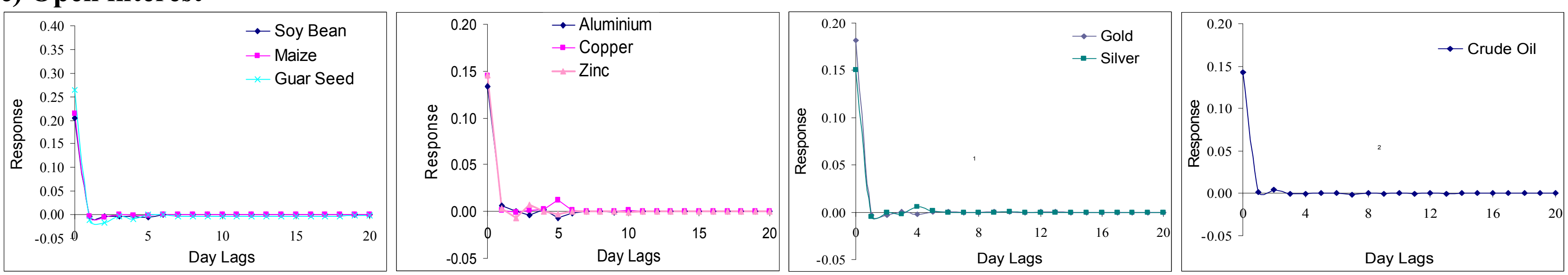
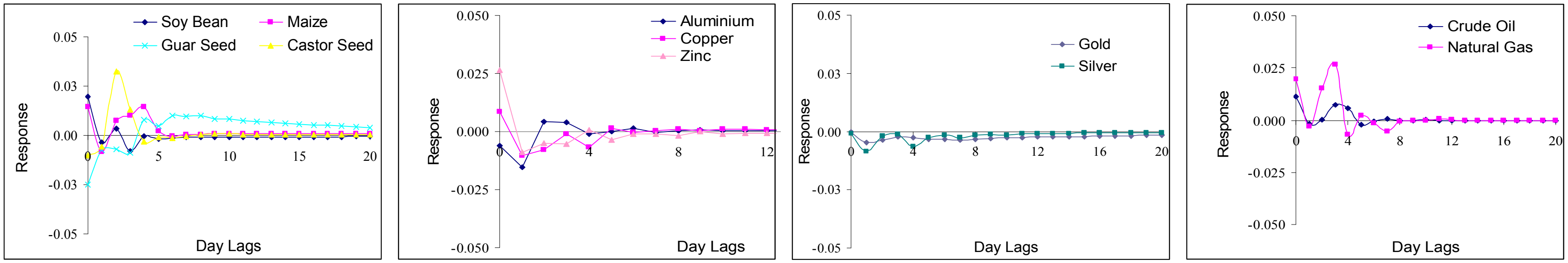
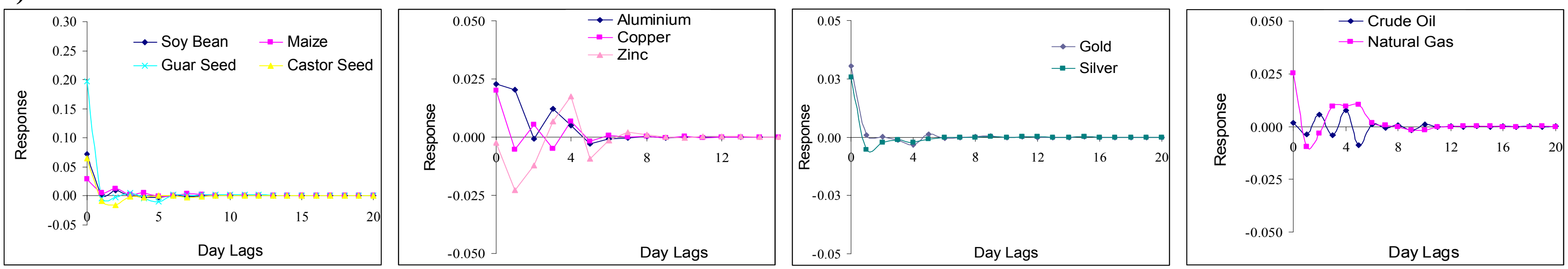


Figure 8: Impulse Response Function for Commodity Futures Open Interest Response to Shock in a) To Close-To-Open Volatility, b) Volume and c) Open Interest Shock

a) Volatility



b) Volume



c) Open interest

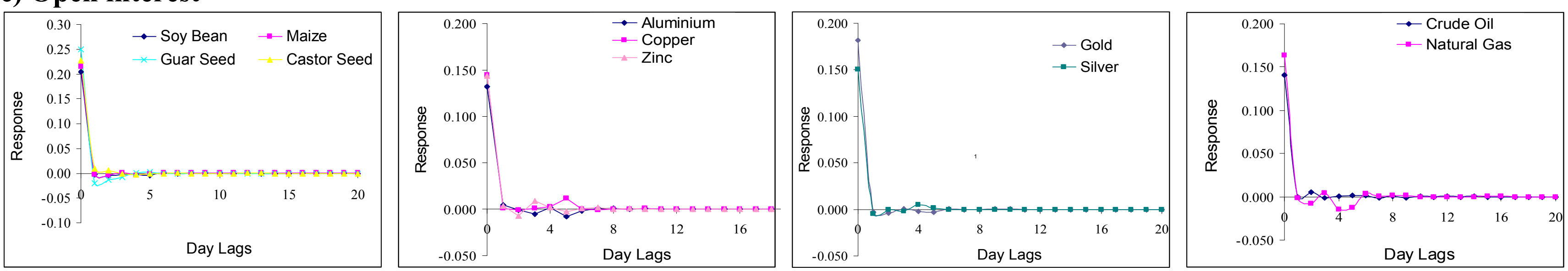
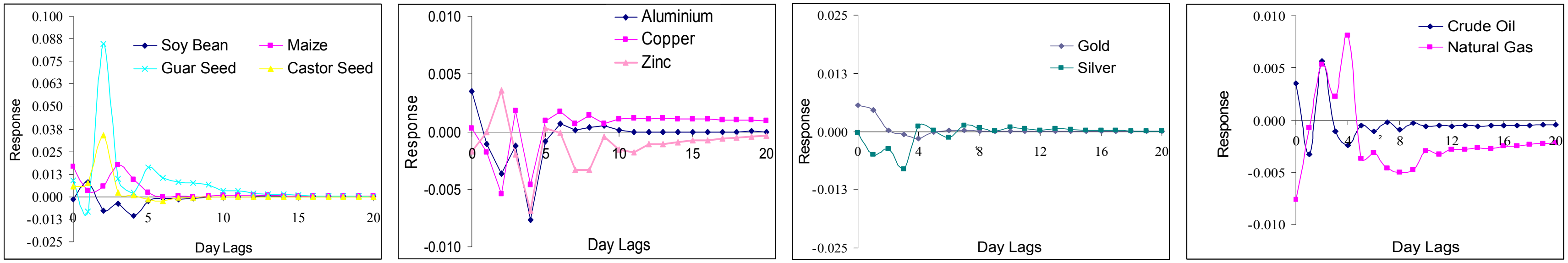
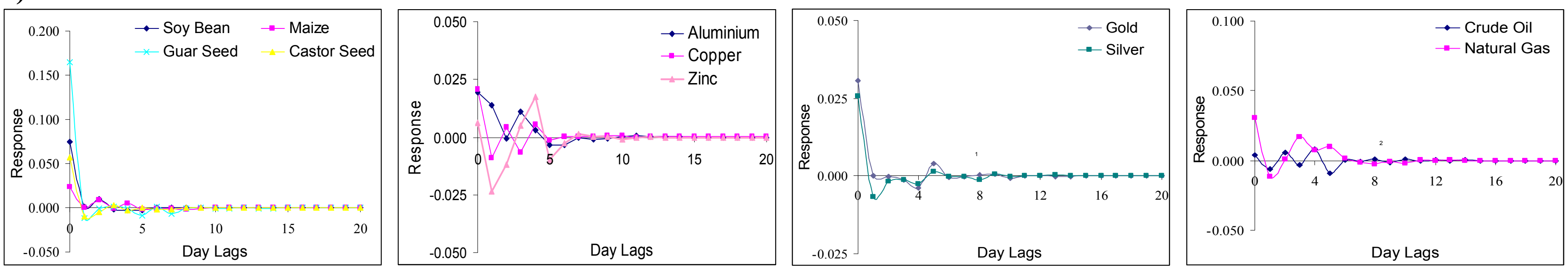


Figure 9: Impulse Response Function For Commodity Futures Open Interest Response To Shock In A) To Open-To-Close Volatility, B) Volume And C) Open Interest Shock

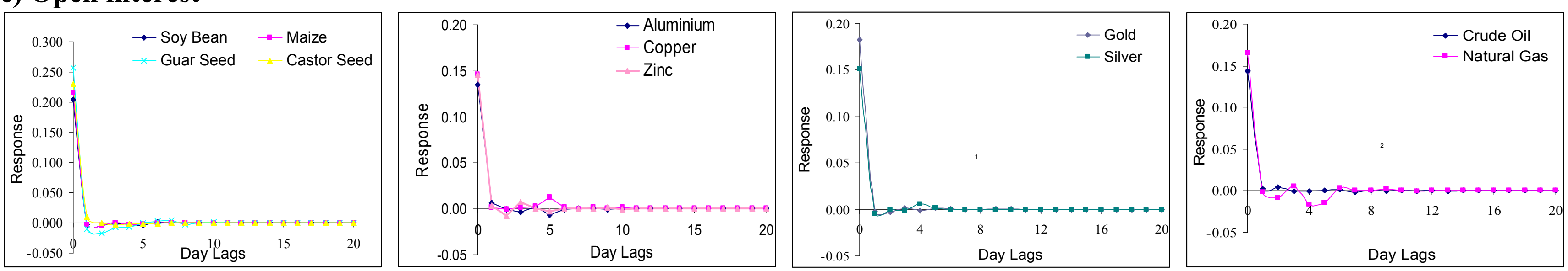
a) Volatility



b) Volume



c) Open interest



Open Interest
Near Month Future

It is important to note that it takes 4-5 days for the volatility shock on volume to die down while it takes at least around 12-15 days for volume shock on volatility to die. This result is more prominent in case of next to near month futures (see appendix). The effect of open interest shock on volatility diminishes after 5-10 days and in initial days, volume shows positive response to this shock. However, we also find some alternate positive- negative responses of volatility to shock in open interest.

Figure 7-9 shows the effect of volatility, volume and lagged open interest shock on open interest. In case of Maize and Guar seed, trading volatility shock generates positive response where as non-trading volatility does not have sizable impact of volatility shock on open interest. In case of metals, non-trading volatility creates negative response of open interest but dies out very soon (5 lags). Bullions and energy commodities do not have substantial effect of volatility shock on open interest. Effect of volume shock on open interest is high and significant but stabilizes after 3-4 lags. Our results related to the dynamic relationship between volume and open interest contradict the findings of Bessembinder et al. (1996) in which open interest and futures trading volume affect each other and the reported effect is persistent in nature.

4. Conclusions

Interaction among return volatility, trading volume and open interest of futures contracts has been the subject of investigation by many researchers. Given that spot and futures prices are linked, many a time futures trading is alleged to be destabilizing spot market, especially in the emerging market context. In this paper, empirical evidence is provided on the contemporaneous as well as dynamic relationship across return volatility, volume and open interest in the Indian commodity futures market. Understanding these relationships will be helpful for investors, traders and policy makers. We consider four agricultural commodities- Soybean, Maize, Castor seed, and Guar seed, three metals- Aluminum, Copper and Zinc, two bullions- Gold and Silver, and two energy commodities- Crude oil and Natural gas for the analysis. Three measures of volatility: daily volatility measured by close-to-close returns, non-trading volatility measured by close-to-open returns and trading volatility measured by open-to-close return is used to compare the interrelation of trading and offshore (non-trading) volatility and trading activity.

The contemporaneous relation between futures volatility and trading activity is investigated through GARCH model in which volatility equation is augmented with trading volume and open interest. As suggested by Bessembinder and Seguin (1993), we divide the trading volume and open interest into expected and unexpected components. The results indicate that all three measures of volatility, volume and open interest are highly autoregressive. The results of contemporaneous relationship between volatility and trading volume indicate that volume (expected or unexpected) positively affects the volatility. This result is consistent with findings of Bessembinder and Seguin (1993) and Karpoff (1987). However, we do find any contemporaneous relationship between open interest and volatility.

The dynamic relationship across volatility, volume and market depth (open interest) is investigated using vector autoregressive analysis (VAR model). We perform three different types of analyses: Granger causality test, variance decomposition and impulse response function. The

Granger causality test results of dynamic relationship among volatility, the unexpected volume and the unexpected open interest indicate that for agricultural commodities, there exist bi-directional causality between volatility and trading volume. For most of the other non-agricultural commodities, volume Granger causes the volatility. In very few cases we find significant lead-lag relationship between open interest and volatility. We also find that open interest does not affect volume however, lagged volume explains around 30-50% of variation in the open interest (mostly in case of non-agricultural commodities). Furthermore, we observe that return volatility has some predictive power in explaining trading volume, but not open interest. This result is consistent with Schwert (1990) and Gallant et al. (1992), but in contrast to the findings in Bessembinder and Seguin (1993) and Chen et al. (1995), who find a significant contemporaneous relationship between open interest and volatility.

Interestingly, we observe that over night volatility affects volume more than the trading volatility. The effect is positive except in case of metals where trading volume affects the overnight volatility negatively. In other commodities, we find alternate positive-negative effect of over night volatility on volume. We also found that both trading and overnight volatility affects the open interest negatively. This has an important implication for Indian commodity markets where trading volume is less and market is more exposed to information from international markets rather than local information. Developed markets show significant effect of market depth on volatility and persistent effect of open interest on volume. However, in Indian commodity derivatives markets, effect of market depth on futures volatility is insignificant. Further, we also find asymmetric relationship between volume and market depth and effect of open interest on volume is meager. This raises question about the type of participants and its risk management efficiency of commodity futures market in India. To answer this and understand the linkage between international and Indian markets further research is called for.

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Appendix

Table 1 (a): GARCH Model With Close-To-Close Volatility and Expected and Unexpected Trading Volume and Open Interest (1 Lag of Unexpected Volume and Open Interest Are Also Used)

Commodity			Sum Of AR	α	α_1	β_1	$\alpha_1+\beta_1$	γ	[illegible]	[illegible]	λ	[illegible]	[illegible]$_2$
Agricultural	Soy Bean	Near Futures$^{\Delta}$	0.008	0.246	0.243	0.578	0.820	0.000	0.729	0.005	0.000	0.263	0.001
		Next To Near Future	-0.045	0.000*	0.283*	0.439*	0.722	0.337*	0.339*	0.000	0.000	0.105	0.000
	Maize	Near Futures	-0.053	0.001	0.255*	0.017	0.273	0.903*	0.914*	0.000	0.000	0.000	0.000
		Next To Near Future	-0.086	0.173*	0.213*	0.639*	0.852	0.014	0.491*	0.000	0.000	0.000	0.000
	Castor Seed	Near Futures	-0.076	0.596*	0.074*	0.000	0.074	0.357*	0.607*	0.000	0.000	0.000	0.000
		Next To Near Future	0.003	0.169#	0.058#	0.089	0.147	0.494*	0.770*	0.000	0.025	0.000	0.000
	Guar Seed	Near Futures$^{\Delta}$	-0.026	1.753	0.226	0.118	0.344	0.361	1.964	0.999	0.000	0.001	0.056
		Next To Near Future$^{\Delta}$	-0.029	1.481	0.060	0.001	0.061	1.895	3.974	0.000	0.000	0.051	0.174
Bullion	Gold	Near Futures$^{\Delta}$	0.007	0.999	0.252	0.154	0.407	0.003	0.325	0.000	0.000	0.009	0.006
		Next To Near Future	-0.066	0.002*	0.050*	0.951*	1.002	0.000	0.014*	0.000	0.000	0.000	0.000
	Silver	Near Futures$^{\Delta}$	0.023	2.805	0.334	0.472	0.805	0.079	1.022	0.002	0.008	0.090	0.632
		Next To Near Future	-0.017	0.043*	0.133	0.863*	0.996	0.000	0.064*	0.000	0.000	0.000	0.000
Metals	Aluminium	Near Futures$^{\Delta}$	-0.005	0.162	0.061	0.030	0.091	1.211	1.432	0.009	0.077	0.042	0.000
		Next To Near Future	0.047	0.911*	0.152	0.390*	0.542	0.000	0.973*	0.000	0.000	0.000	0.000
	Copper	Near Future$^{\Delta}$s	0.144	3.107	0.004	0.001	0.004	0.000	1.608	0.000	0.000	0.188	0.000
		Next To Near Future$^{\Delta}$	-0.034	3.063	0.099	0.052	0.151	0.009	0.603	0.093	0.008	0.000	0.035
	Zinc	Near Futures$^{\Delta}$	0.007	1.964	0.008	0.005	0.013	1.750	2.534	0.000	0.072	0.032	0.214
		Next To Near Future$^{\Delta}$	0.020	1.796	0.006	0.181	0.186	4.895	8.037	0.000	0.000	0.000	0.000
Energy	Crude Oil	Near Futures	0.035	1.546*	0.033*	0.005	0.038	1.942*	2.461*	0.158*	0.074*	0.465*	0.000
		Next To Near Future	0.021	1.259*	0.151*	0.258*	0.409	0.401#	1.396*	0.000	0.027	0.000	0.000
	Natural Gas	Near Futures$^{\Delta}$	0.025	2.109	0.001	0.033	0.033	3.354	4.680	0.515	0.005	0.121	0.002
		Next To Near Future	-0.040	3.005*	0.000	0.000	0.000	1.806*	2.118*	0.000	0.086	0.000	0.000

$^{\Delta}$ Did not converge and value after the last iteration is presented.

*, #, $ significant at 1, 5 and 10% level respectively

Table 1 (b): GARCH Model with Close-To-Open Volatility and Expected and Unexpected Trading Volume and Open Interest (1 Lag of Unexpected Volume and Open Interest Are Also Used)

Commodity			Sum Of AR	α	α_1	β_1	$\alpha_1+\beta_1$	γ	[illegible]	[illegible]	λ	[illegible]	[illegible]$_2$
Agricultural	Soy Bean	Near Futures	-0.322	0.031*	0.094*	0.884*	0.977	0.000	0.078$	0.000	0.000	0.000	0.022
		Next To Near Future	-0.306	0.029	0.084*	0.900*	0.984	0.010	0.013	0.000	0.010	0.000	0.000
	Maize	Near Futures	-0.375	0.000	0.092*	0.885*	0.977	0.044*	0.051*	0.000	0.000	0.010	0.000
		Next To Near Future	-0.354	0.088#	0.133*	0.803*	0.936	0.000	0.192#	0.024	0.017	0.000	0.000
	Castor Seed	Near Futures	-0.317	0.147*	0.098*	0.845*	0.943	0.000	0.082	0.000	0.000	0.008	0.000
		Next To Near Future	-0.297	0.046*	0.067*	0.893*	0.960	0.000	0.058	0.000	0.000	0.120	0.144
	Guar Seed	Near Futures	-0.327	0.219*	0.123*	0.827*	0.951	0.000	0.377*	0.000	0.000	0.000	0.000
		Next To Near Future	-0.341	0.033	0.076*	0.887*	0.963	0.073	0.415*	0.000	0.053	0.000	0.000
Bullion	Gold	Near Futures	-0.395	0.020*	0.129*	0.862*	0.991	0.000	0.000	0.000	0.000	0.000	0.000
		Next To Near Future	-0.399	0.000	0.096*	0.902*	0.998	0.008*	0.000	0.000	0.000	0.000	0.000
	Silver	Near Futures	-0.395	0.116	0.146*	0.848*	0.993	0.000	0.019	0.000	0.000	0.000	0.000
		Next To Near Future	-0.397	0.129*	0.249*	0.749*	0.998	0.000	0.037*	0.000	0.000	0.000	0.000
Metals	Aluminium	Near Futures	-0.352	0.090#	0.097*	0.874*	0.970	0.000	0.027	0.017	0.000	0.000	0.000
		Next To Near Future	-0.315	0.103*	0.082*	0.898*	0.980	0.000	0.058	0.050	0.000	0.000	0.485
	Copper	Near Futures	-0.337	0.000	0.083*	0.893*	0.976	0.000	0.000	0.000	0.100#	0.000	0.286
		Next To Near Future	-0.319	0.148$	0.106*	0.858*	0.964	0.000	0.037	0.011	0.000	0.000	0.000
	Zinc	Near Futures	-0.372	5.378*	0.117*	0.014	0.132	0.000	0.272	0.000	0.000	0.000	0.000
		Next To Near Future	-0.395	0.419#	0.084*	0.841*	0.925	0.000	0.113	0.000	0.000	0.000	0.000
Energy	Crude Oil	Near Futures	-0.342	0.000	0.035*	0.967*	1.002	0.000	0.000	0.000	0.004	0.000	0.128
		Next To Near Future	-0.323	0.002	0.045*	0.954*	0.999	0.000	0.000	0.000	0.010	0.000	0.000
	Natural Gas	Near Futures	-0.373	0.220	0.048#	0.931*	0.979	0.000	0.174	0.067	0.000	0.000	0.000
		Next To Near Future $^{\Delta}$	-0.370	0.000	0.000	1.000	1.000	0.011	0.247	0.044	0.000	0.132	0.000

$^{\Delta}$ Did not converge and value after the last iteration is presented.

*, #, $ significant at 1, 5 and 10% level respectively

Table 1 (c): GARCH Model with Open-To-Close Volatility and Expected and Unexpected Trading Volume and Open Interest (1 Lag of Unexpected Volume and Open Interest Are Also Used)

Commodity			Sum Of AR	α	α_1	β_1	$\alpha_1+\beta_1$	γ	[illegible]	[illegible]	λ	[illegible]	[illegible]$_2$
Agricultural	Soy Bean	Near Futures	-0.007	0.005*	0.134*	0.842*	0.975	0.000	0.000	0.011$	0.000	0.000	0.000
		Next To Near Future	-0.071	0.000	0.213*	0.780*	0.993	0.004 Δ	0.000	0.004$	0.000	0.008	0.000
	Maize	Near Futures	-0.099	0.169*	0.120*	0.000	0.120	0.079*	0.063*	0.028 Δ	0.000	0.000	0.000
		Next To Near Future	-0.066	0.009*	0.069*	0.909*	0.978	0.000	0.020*	0.001	0.000	0.000	0.003
	Castor Seed	Near Futures	0.020	0.010	0.072*	0.870*	0.942	0.002	0.000	0.000	0.000	0.000	0.000
		Next To Near Future	0.033	0.005*	0.073*	0.904*	0.976	0.000	0.001	0.000	0.000	0.000	0.000
	Guar Seed	Near Futures	-0.073	0.006*	0.278*	0.744*	1.021	0.000	0.000	0.021*	0.000	0.000	0.000
		Next To Near Future	-0.031	0.000	0.243*	0.740*	0.983	0.008*	0.008	0.006	0.000	0.000	0.000
Bullion	Gold	Near Futures	0.004	0.002*	0.183*	0.827*	1.010	0.000	0.000	0.001*	0.000	0.000	0.000
		Next To Near Future	0.096	0.008*	0.345*	0.666*	1.011	0.001*	0.000	0.000	0.000	0.000	0.000
	Silver	Near Futures	0.062	0.012*	0.181*	0.799*	0.980	0.000	0.001	0.004*	0.000	0.000	0.000
		Next To Near Future	-0.023	0.000	0.092*	0.912*	1.004	0.001*	0.000	0.000	0.000	0.000	0.000
Metals	Aluminium	Near Futures	0.041	0.003	0.113*	0.882*	0.995	0.003	0.009*	0.000	0.000	0.000	0.000
		Next To Near Future	0.026	0.004*	0.082*	0.917*	0.999	0.000	0.000	0.017*	0.000	0.000	0.000
	Copper	Near Future Δ s	-0.075	0.053	0.146	0.057	0.203	0.001	0.044	0.023	0.016	0.002	0.000
		Next To Near Future Δ	-0.077	0.199	0.213	0.006	0.219	0.000	0.033	0.004	0.000	0.000	0.007
	Zinc	Near Futures	-0.087	0.018#	0.205*	0.707*	0.912	0.003	0.020*	0.000	0.004	0.010	0.000
		Next To Near Future	-0.018	0.005*	0.111*	0.874*	0.985	0.000	0.000	0.004$	0.000	0.000	0.000
Energy	Crude Oil	Near Futures	0.007	0.000	0.018*	0.963*	0.981	0.001$	0.000	0.001	0.000	0.000	0.000
		Next To Near Future	-0.007	0.000	0.062*	0.938*	1.000	0.001$	0.000	0.000	0.000	0.000	0.000
	Natural Gas	Near Futures	-0.049	0.006	0.060*	0.930*	0.990	0.003	0.000	0.017	0.000	0.000	0.072
		Next To Near Future Δ	-0.006	0.460*	0.305*	0.164	0.469	0.001	0.048*	0.000	0.000	0.000	0.000

Δ Did not converge and value after the last iteration is presented.

*, #, $ significant at 1, 5 and 10% level respectively

Table 2(a) VAR Model with Close-To-Close Return Volatility, Volume and Open Interest for Next To Near Contracts

	Volatility															
	a_1	$b_{1,1}$	$b_{1,2}$	$b_{1,3}$	$b_{1,4}$	$b_{1,5}$	$c_{1,1}$	$c_{1,2}$	$c_{1,3}$	$c_{1,4}$	$c_{1,5}$	$d_{1,1}$	$d_{1,2}$	$d_{1,3}$	$d_{1,4}$	$d_{1,5}$
Soy Bean	0.04	0.97^{*}	$0.08^{\$}$	-0.01	-0.14^{*}	0.09^{*}	0.06^{*}	-0.02^{*}	0.01	-0.01	0.00	0.22^{*}	-0.02^{*}	-0.07	0.05	0.02
Maize	0.03	0.92^{*}	$0.08^{\$}$	-0.04	-0.12^{*}	0.08^{*}	0.13^{*}	0.00	0.04	0.06^{*}	$0.03^{\#}$	0.07	0.01	-0.03	$-0.17^{\#}$	-0.07
Castor Seed	0.02^{*}	0.81^{*}	0.11^{*}	0.05	0.03	-0.03	0.07^{*}	0.01^{*}	-0.03	0.00	0.00	-0.01	0.01	$-0.04^{\$}$	0.02	0.01
Guar Seed	0.11^{*}	0.96^{*}	-0.04	0.06	0.03	-0.04	0.75^{*}	-0.05	-0.02	0.02	$0.08^{\#}$	-0.98^{*}	0.19^{*}	-0.46	$-0.26^{\#}$	-0.10
Gold	$0.01^{\#}$	1.06^{*}	$0.09^{\#}$	-0.19^{*}	0.03	-0.01	0.01^{*}	0.00	-0.01	0.00	0.00	-0.01	0.00	-0.01	0.01	0.01
Silver	0.18^{*}	1.06^{*}	-0.13^{*}	0.22^{*}	-0.20^{*}	-0.01	0.04	0.02	-0.05	0.01	0.02	-0.01	0.02	-0.09	$-0.16^{\$}$	-0.09
Aluminium	0.08^{*}	0.98^{*}	-0.06	$0.12^{\#}$	-0.02	$-0.06^{\$}$	0.08^{*}	-0.01	-0.02	-0.01	-0.01	-0.04	-0.01	0.01	-0.01	0.11
Copper	$0.08^{\#}$	0.92^{*}	0.12^{*}	-0.07	0.04	-0.04	0.10^{*}	$0.04^{\$}$	$-0.15^{\#}$	0.00	-0.03	-0.17^{*}	0.00	-0.05	-0.10	0.04
Zinc	0.15^{*}	0.96^{*}	0.02	-0.04	0.08	-0.04	0.12^{*}	0.02	$-0.09^{\#}$	-0.01	-0.06^{*}	-0.20^{*}	0.01	-0.04	-0.02	$0.08^{\#}$
Crude Oil	-0.01^{*}	1.03^{*}	$-0.08^{\$}$	0.04	0.06	-0.05	0.04^{*}	0.01	-0.01	0.00	0.00	-0.06^{*}	0.00	-0.02	0.00	-0.01
Natural Gas																
	Volume															
	$\mathbf{a_2}$	$\mathbf{b_{2,1}}$	$\mathbf{b_{2,2}}$	$\mathbf{b_{2,3}}$	$\mathbf{b_{2,4}}$	$\mathbf{b_{2,5}}$	$\mathbf{c_{2,1}}$	$\mathbf{c_{2,2}}$	$\mathbf{c_{2,3}}$	$\mathbf{c_{2,4}}$	$\mathbf{c_{2,5}}$	$\mathbf{d_{2,1}}$	$\mathbf{d_{2,2}}$	$\mathbf{d_{2,3}}$	$\mathbf{d_{2,4}}$	$\mathbf{d_{2,5}}$
Soy Bean	-0.44^{*}	-0.20	-0.05	0.01	-0.15	0.38^{*}	0.18^{*}	0.18^{*}	-0.17	0.15^{*}	0.25^{*}	-0.12	0.19^{*}	-0.05	0.15	0.10
Maize	0.13	0.04	$-0.30^{\#}$	0.20	0.02	0.05	-0.02	0.00	0.19	0.02	-0.03	0.43	0.02	-0.07	0.04	-0.25
Castor Seed	$0.12^{\#}$	-0.08	-0.28	0.29	-0.30	0.25	-0.05	-0.02	$0.32^{\$}$	-0.03	0.03	0.68^{*}	-0.01	0.15	0.45^{*}	0.14
Guar Seed	0.02	$-0.07^{\#}$	-0.04	0.21^{*}	$-0.08^{\$}$	-0.03	-0.07	0.06	0.11	-0.12^{*}	-0.04	0.72^{*}	0.02	0.19	$0.31^{\#}$	-0.03
Gold	-0.02	-0.34	0.07	0.13	0.16	-0.01	-0.26^{*}	-0.22^{*}	0.80^{*}	-0.14^{*}	$-0.05^{\$}$	1.03^{*}	-0.18^{*}	0.81^{*}	0.79^{*}	0.41
Silver	$0.22^{\#}$	-0.03	0.02	0.02	-0.05	0.04	-0.21^{*}	-0.11^{*}	0.65^{*}	$-0.06^{\$}$	-0.10^{*}	1.24^{*}	-0.17^{*}	1.05^{*}	0.81^{*}	0.54^{*}
Aluminium	-0.01	0.14	$-0.33^{\#}$	0.09	-0.18	0.31^{*}	-0.22^{*}	-0.02	$0.25^{\#}$	0.04	0.06	0.40^{*}	-0.06	0.36^{*}	0.35^{*}	0.09
Copper	0.00	-0.09	0.13	-0.04	0.05	-0.04	-0.35^{*}	-0.15^{*}	0.74^{*}	-0.06	-0.05	1.29^{*}	$-0.08^{\$}$	0.55^{*}	0.36^{*}	0.33^{*}
Zinc	0.08	-0.17	0.04	0.08	0.03	0.00	-0.33^{*}	-0.06	0.36^{*}	-0.07	-0.01	0.76^{*}	-0.06	$0.28^{\#}$	$0.28^{\#}$	$0.24^{\#}$
Crude Oil	-0.07	-0.09	0.38	0.25	$-0.93^{\#}$	0.43	-0.41^{*}	-0.31^{*}	0.76^{*}	-0.17^{*}	$-0.11^{\#}$	0.79^{*}	$-0.14^{\#}$	0.47^{*}	0.48^{*}	0.49^{*}
Natural Gas																
	open interest															
	$\mathbf{a_3}$	$\mathbf{b_{3,1}}$	$\mathbf{b_{3,2}}$	$\mathbf{b_{3,3}}$	$\mathbf{b_{3,4}}$	$\mathbf{b_{3,5}}$	$\mathbf{c_{3,1}}$	$\mathbf{c_{3,2}}$	$\mathbf{c_{3,3}}$	$\mathbf{c_{3,4}}$	$\mathbf{c_{3,5}}$	$\mathbf{d_{3,1}}$	$\mathbf{d_{3,2}}$	$\mathbf{d_{3,3}}$	$\mathbf{d_{3,4}}$	$\mathbf{d_{3,5}}$
Soy Bean	0.01	0.00	0.01	-0.02	0.02	-0.01	0.00	0.00	0.02	0.00	0.00	0.04	-0.01	-0.01	0.00	-0.01
Maize	-0.06^{*}	0.01	$-0.04^{\#}$	0.06^{*}	0.01	-0.05^{*}	-0.01	0.01	0.15^{*}	0.00	$-0.01^{\#}$	0.12^{*}	$-0.01^{\#}$	0.22^{*}	0.18^{*}	0.17^{*}
Castor Seed	0.00	0.04	0.01	$-0.13^{\#}$	$0.14^{\#}$	-0.07	-0.01	$0.01^{\#}$	0.00	0.00	-0.01	0.03	0.00	0.03	0.01	-0.01
Guar Seed	-0.01	0.00	0.00	0.01	0.00	-0.01	-0.01	0.01	-0.01	0.00	0.00	0.01	0.00	-0.02	0.00	-0.02
Gold	0.01	-0.10	0.05	0.06	-0.02	-0.01	0.02	-0.04^{*}	0.05	-0.05^{*}	-0.05^{*}	-0.04	$-0.02^{\#}$	$0.06^{\$}$	0.12^{*}	$0.07^{\#}$
Silver	$-0.06^{\#}$	0.00	0.00	0.01	-0.01	0.00	-0.02	0.03^{*}	$-0.08^{\#}$	$-0.02^{\#}$	-0.05	0.00	0.00	-0.05	-0.01	0.04
Aluminium	$-0.05^{\$}$	0.06	0.01	-0.06	$-0.12^{\#}$	$0.10^{\#}$	-0.12^{*}	-0.05^{*}	0.05	-0.04^{*}	-0.06^{*}	0.02	0.00	-0.03	0.09^{*}	0.14^{*}
Copper	-0.01	0.01	0.00	-0.04	0.03	-0.01	-0.10^{*}	-0.06^{*}	0.13^{*}	-0.04^{*}	-0.02	0.14^{*}	-0.07^{*}	0.15^{*}	0.19^{*}	$0.10^{\#}$
Zinc	0.06	-0.05	-0.01	0.06	0.01	-0.02	-0.15^{*}	-0.08^{*}	$0.11^{\#}$	-0.08^{*}	$-0.04^{\$}$	0.20^{*}	-0.08^{*}	$0.12^{\#}$	0.15^{*}	0.14^{*}
Crude Oil	-0.04	0.02	0.08	0.16	-0.31	0.06	-0.23^{*}	-0.17^{*}	0.30^{*}	-0.10^{*}	-0.11^{*}	0.29^{*}	-0.10^{*}	0.20^{*}	0.19^{*}	0.28^{*}
Natural Gas																

*, #, $\$$ significant at 1, 5 and 10% level respectively

Table 2(b) VAR Model with Close-To-Open Return Volatility, Volume and Open Interest for Next To Near Contracts

								Volatility								
	a_1	**$b_{1,1}$**	**$b_{1,2}$**	**$b_{1,3}$**	**$b_{1,4}$**	**$b_{1,5}$**	**$c_{1,1}$**	**$c_{1,2}$**	**$c_{1,3}$**	**$c_{1,4}$**	**$c_{1,5}$**	**$d_{1,1}$**	**$d_{1,2}$**	**$d_{1,3}$**	**$d_{1,4}$**	**$d_{1,5}$**
Soy Bean	0.02	0.99^{*}	-0.03	$0.09^{\#}$	-0.15^{*}	0.08^{*}	-0.01	-0.01	0.00	0.01	0.01	0.02	-0.05	-0.01	0.02	-0.01
Maize	0.10	0.91^{*}	$-0.08^{\$}$	-0.02	-0.07	0.11^{*}	0.00	0.08^{*}	0.11^{*}	0.09^{*}	0.07^{*}	0.05	0.26	-0.11	-0.13	$-0.40^{\#}$
Castor Seed	0.06^{*}	0.89^{*}	0.01	0.06	0.03	-0.04	0.01	0.01	0.01	0.01	0.01	0.00	$-0.07^{\$}$	0.04	$0.09^{\#}$	0.03
Guar Seed	0.19^{*}	1.09^{*}	-0.14^{*}	0.01	0.05	-0.05	-0.04	0.15^{*}	0.00	0.07	-0.05	0.59^{*}	$-0.42^{\#}$	-0.04	0.16	-0.20
Gold	0.04^{*}	1.00^{*}	0.12^{*}	-0.20^{*}	0.00	$0.06^{\#}$	0.00	-0.01	-0.01	0.00	0.00	0.01	-0.01	0.04	0.01	-0.02
Silver	0.42^{*}	0.91^{*}	-0.06	0.26^{*}	-0.25^{*}	0.03	0.03	0.04	0.04	0.01	0.01	-0.11	-0.12	-0.24	-0.14	-0.13
Aluminium	0.14^{*}	1.02^{*}	-0.04	0.12	-0.17^{*}	0.03	-0.02	-0.03	0.00	-0.02	0.01	-0.01	0.06	-0.05	0.28^{*}	0.04
Copper	$0.23^{\#}$	1.00^{*}	-0.03	$-0.11^{\$}$	$0.13^{\#}$	-0.05	0.01	$-0.05^{\$}$	0.00	0.01	-0.04	-0.10	-0.10	0.02	$-0.29^{\#}$	0.04
Zinc	0.30^{*}	0.95^{*}	-0.03	-0.03	$0.09^{\$}$	-0.04	0.07	0.03	0.06	$-0.07^{\$}$	-0.01	-0.10	-0.02	-0.08	0.07	0.05
Crude Oil	-0.01	0.96^{*}	-0.06	0.14^{*}	0.07	-0.10^{*}	0.01	0.01	0.00	0.00	0.01	-0.01	-0.02	0.00	0.01	-0.01
Natural Gas	0.23^{*}	0.96^{*}	0.01	-0.05	0.02	0.01	0.01	$0.04^{\#}$	$0.03^{\$}$	0.06^{*}	$0.03^{\$}$	0.04	-0.04	-0.04	-0.03	-0.15^{*}
								Volume								
	a_2	**$b_{2,1}$**	**$b_{2,2}$**	**$b_{2,3}$**	**$b_{2,4}$**	**$b_{2,5}$**	**$c_{2,1}$**	**$c_{2,2}$**	**$c_{2,3}$**	**$c_{2,4}$**	**$c_{2,5}$**	**$d_{2,1}$**	**$d_{2,2}$**	**$d_{2,3}$**	**$d_{2,4}$**	**$d_{2,5}$**
Soy Bean	-0.45^{*}	0.08	-0.27^{*}	0.06	-0.05	$0.17^{\#}$	0.18^{*}	0.18^{*}	0.19^{*}	0.15^{*}	0.24^{*}	-0.14	-0.14	-0.06	0.14	0.05
Maize	0.12	0.11^{*}	-0.10	$-0.11^{\$}$	0.05	0.05	-0.04	0.00	0.00	0.01	-0.03	0.35	0.20	-0.09	0.06	-0.21
Castor Seed	$0.10^{\$}$	$0.26^{\$}$	-0.47^{*}	-0.02	0.22	-0.08	-0.08	0.00	-0.01	-0.04	0.01	0.72^{*}	$0.33^{\#}$	0.15	0.43^{*}	0.13
Guar Seed	0.01	0.03	$-0.07^{\#}$	0.03	0.05	$-0.04^{\$}$	-0.08	0.03	-0.05	$-0.07^{\#}$	$-0.05^{\$}$	0.74^{*}	0.19	$0.31^{\#}$	$0.24^{\$}$	-0.01
Gold	-0.02	-0.03	-0.02	-0.10	0.06	0.10	-0.26^{*}	-0.22^{*}	-0.18^{*}	-0.14^{*}	$-0.05^{\$}$	1.03^{*}	0.80^{*}	0.82^{*}	0.80^{*}	0.42^{*}
Silver	0.25^{*}	-0.02	-0.01	0.01	0.01	0.01	-0.21^{*}	-0.11^{*}	-0.17^{*}	-0.06	-0.10^{*}	1.24^{*}	0.64^{*}	1.05^{*}	0.80^{*}	0.53^{*}
Aluminium	-0.01	$0.18^{\#}$	$-0.20^{\$}$	0.00	-0.01	0.05	-0.22^{*}	-0.01	$-0.08^{\#}$	0.02	0.03	0.40^{*}	$0.21^{\#}$	0.25^{*}	0.32^{*}	0.06
Copper	0.01	0.04	$-0.11^{\$}$	0.07	-0.01	0.00	-0.35^{*}	-0.15^{*}	-0.07	-0.06	-0.05	1.29^{*}	0.76^{*}	0.56^{*}	0.37^{*}	$0.33^{\#}$
Zinc	0.03	$0.13^{\#}$	$-0.18^{\#}$	0.02	-0.02	0.04	-0.35^{*}	-0.08	-0.07	-0.07	0.00	0.79^{*}	0.39^{*}	0.30^{*}	$0.28^{\#}$	$0.22^{\#}$
Crude Oil	0.03	$-0.36^{\#}$	0.31	0.33	0.17	$-0.46^{\#}$	-0.38^{*}	-0.29^{*}	$-0.14^{\#}$	-0.18^{*}	$-0.12^{\#}$	0.73^{*}	0.72^{*}	0.44^{*}	0.48^{*}	0.50^{*}
Natural Gas	0.17	-0.24^{*}	0.28^{*}	-0.11	0.09	-0.06	-0.24^{*}	-0.25^{*}	0.02	-0.13^{*}	-0.13^{*}	0.55^{*}	0.50^{*}	-0.07	0.37^{*}	0.27^{*}
								open interest								
	a_3	**$b_{3,1}$**	**$b_{3,2}$**	**$b_{3,3}$**	**$b_{3,4}$**	**$b_{3,5}$**	**$c_{3,1}$**	**$c_{3,2}$**	**$c_{3,3}$**	**$c_{3,4}$**	**$c_{3,5}$**	**$d_{3,1}$**	**$d_{3,2}$**	**$d_{3,3}$**	**$d_{3,4}$**	**$d_{3,5}$**
Soy Bean	0.01	$0.02^{\$}$	-0.03	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.02	-0.01	0.00	-0.01
Maize	-0.06^{*}	0.00	0.00	$-0.02^{\#}$	0.03	-0.01	-0.01	0.01	$-0.01^{\#}$	0.00	0.00	0.13^{*}	0.15^{*}	0.22^{*}	0.18^{*}	0.17^{*}
Castor Seed	0.00	$0.06^{\#}$	-0.01	-0.01	$-0.08^{\#}$	$0.05^{\$}$	-0.02	$0.01^{\$}$	0.00	0.00	0.00	0.03	0.01	0.04	0.01	-0.02
Guar Seed	-0.01	-0.01	0.00	0.01	0.00	0.00	-0.01	$0.02^{\$}$	0.00	0.00	0.00	0.00	-0.01	-0.01	-0.01	-0.02
Gold	0.01	0.01	-0.06	0.03	0.03	-0.02	0.02	-0.04^{*}	$-0.02^{\#}$	-0.05^{*}	-0.05^{*}	-0.04	0.05	$0.06^{\$}$	0.12^{*}	$0.08^{\#}$
Silver	$-0.06^{\#}$	0.00	0.00	0.00	0.00	0.00	-0.02	0.03^{*}	0.00	$-0.02^{\#}$	-0.05^{*}	0.00	$-0.08^{\#}$	-0.05	-0.01	0.04
Aluminium	$-0.04^{\$}$	$0.06^{\#}$	-0.04	0.01	-0.04	-0.01	-0.12^{*}	-0.04^{*}	0.00	-0.04^{*}	-0.06	0.01	0.03	-0.01	0.08^{*}	0.13^{*}
Copper	-0.02	0.01	-0.01	0.00	-0.01	0.01	-0.10^{*}	-0.06^{*}	-0.06^{*}	-0.04^{*}	-0.02	0.14^{*}	0.13^{*}	0.15^{*}	0.19^{*}	$0.10^{\#}$
Zinc	0.02	0.08^{*}	-0.11^{*}	0.01	0.01	0.00	-0.16^{*}	-0.09^{*}	-0.09^{*}	-0.08^{*}	-0.03	0.22^{*}	$0.13^{\#}$	$0.13^{\#}$	0.16^{*}	$0.13^{\#}$
Crude Oil	0.00	0.03	-0.01	0.13	0.03	$-0.18^{\#}$	-0.22^{*}	-0.16^{*}	-0.10^{*}	-0.10^{*}	-0.11^{*}	0.27^{*}	0.29^{*}	0.20^{*}	0.20^{*}	0.28^{*}
Natural Gas	0.06	-0.09^{*}	0.17^{*}	$-0.09^{\#}$	0.05	-0.04	-0.01	-0.13^{*}	-0.02	-0.06^{*}	-0.07^{*}	0.02	0.22^{*}	-0.04	0.13^{*}	0.10^{*}

*, #, $ significant at 1, 5 and 10% level respectively

Table2(c) VAR Model with Close-To-Open Return Volatility, Volume and Open Interest for Next To Near Contracts

	Volatility															
	a_1	$b_{1,1}$	$b_{1,2}$	$b_{1,3}$	$b_{1,4}$	$b_{1,5}$	$c_{1,1}$	$c_{1,2}$	$c_{1,3}$	$c_{1,4}$	$c_{1,5}$	$d_{1,1}$	$d_{1,2}$	$d_{1,3}$	$d_{1,4}$	$d_{1,5}$
Soy Bean	0.02	0.80*	0.07$	-0.02	0.00	0.01	-0.02	0.00	0.01	0.02	-0.01	0.31*	0.07	-0.02	0.06	0.06
Maize	0.01$	1.19*	-0.22*	-0.06	0.04	0.01	0.00	0.00	0.00	0.01*	0.00	-0.01	0.02	0.02	-0.01	-0.02
Castor Seed	0.00*	1.09*	-0.09$	-0.13*	0.06	0.03	0.00	0.00	0.00	0.00	0.00	-0.01	-0.01	-0.01	0.00	-0.01
Guar Seed	0.04*	0.94*	-0.15*	-0.02	0.09#	-0.01	0.07*	0.08*	-0.09*	0.01	0.04#	-0.08	0.17$	-0.02	0.10	-0.20#
Gold	0.08*	0.49*	0.15*	-0.07#	-0.03	0.11*	0.01	0.00	0.00	0.00	-0.01	-0.08*	-0.03	0.00	-0.05$	0.01
Silver	0.01#	1.05#	-0.08	0.11#	-0.11*	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	-0.01	-0.01
Aluminium	0.02*	1.05*	-0.08	-0.06	0.14#	-0.08#	0.00	-0.01$	0.00	0.00	0.00	-0.02*	-0.01	0.01	0.01	0.02*
Copper	0.01*	0.92*	0.08$	0.05	0.05	-0.15*	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	0.01	-0.01	0.00
Zinc	0.01#	0.97*	-0.05	0.10$	-0.11#	0.05	0.00	0.00	0.01$	0.00	0.00	-0.01	0.01	-0.02#	0.00	0.00
Crude Oil	0.00	1.00*	0.02	-0.04	0.08$	-0.07#	0.00	0.01#	0.00	0.00	0.00	-0.01	-0.01#	0.00	-0.01#	0.00
Natural Gas	0.02*	1.08*	-0.12*	0.01	0.00	0.02	0.00	0.00	0.00	-0.01*	0.01*	-0.01	-0.02$	-0.03*	0.01	0.00
	Volume															
	a_2	$b_{2,1}$	$b_{2,2}$	$b_{2,3}$	$b_{2,4}$	$b_{2,5}$	$c_{2,1}$	$c_{2,2}$	$c_{2,3}$	$c_{2,4}$	$c_{2,5}$	$d_{2,1}$	$d_{2,2}$	$d_{2,3}$	$d_{2,4}$	$d_{2,5}$
Soy Bean	-0.46*	-0.09	0.04	0.03	-0.06	0.08	0.20*	0.17*	0.18*	0.15*	0.25*	-0.13	-0.21	-0.11	0.09	0.05
Maize	0.13	-0.54	0.07	1.05	-0.83	0.28	-0.02	-0.01	-0.02	0.02	-0.03	0.41	0.17	-0.06	0.06	-0.26
Castor Seed	0.02	-0.34	1.14	-1.57	0.10	0.57	-0.05	-0.02	-0.03	-0.04	0.00	0.69*	0.29$	0.15	0.45*	0.14
Guar Seed	0.00	-0.09	0.32*	-0.42*	0.33*	-0.15*	-0.04	-0.02	-0.06	-0.06	-0.02	0.77*	0.10	0.39*	0.13	0.08
Gold	0.02	-0.04	0.00	-0.02	-0.05	-0.01	-0.26*	-0.22*	-0.18*	-0.14*	-0.05	1.03*	0.79*	0.81*	0.79*	0.41*
Silver	0.29*	-0.01	-0.52	0.11	-0.26	0.59	-0.21*	-0.11*	-0.18*	-0.06$	-0.10*	1.24*	0.65*	1.05*	0.81*	0.55*
Aluminium	0.01	-0.11	-0.14	-0.06	0.06	0.37	-0.21*	-0.01	-0.09	0.03	0.03	0.38*	0.19$	0.33*	0.31*	0.10
Copper	0.02	-0.62	0.60	-0.89	0.64	0.18	-0.35*	-0.16*	-0.08$	-0.05	-0.05	1.28*	0.76*	0.57*	0.37*	0.34*
Zinc	0.04	-0.34	0.31	-0.36	0.51	-0.27	-0.33*	-0.08	-0.09	-0.08	-0.02	0.74*	0.37*	0.31*	0.30*	0.25
Crude Oil	-0.02	0.29	-0.90	0.55	-1.17	1.34	-0.41*	-0.32*	-0.14	-0.13	-0.12	0.78*	0.78*	0.46*	0.42*	0.50*
Natural Gas	-0.07	-0.49	0.73	-0.80	0.52	0.12	-0.25*	-0.23*	0.03	-0.11*	-0.12*	0.97*	0.67*	-0.01	0.38*	0.32*
	open interest															
	a_3	$b_{3,1}$	$b_{3,2}$	$b_{3,3}$	$b_{3,4}$	$b_{3,5}$	$c_{3,1}$	$c_{3,2}$	$c_{3,3}$	$c_{3,4}$	$c_{3,5}$	$d_{3,1}$	$d_{3,2}$	$d_{3,3}$	$d_{3,4}$	$d_{3,5}$
Soy Bean	0.01	-0.01	0.01	0.00	-0.01	-0.01	0.00	0.00	-0.01	0.00	0.00	0.04	0.02	-0.01	-0.01	-0.01
Maize	-0.06*	0.06	-0.13	0.42*	-0.41*	0.05	-0.01	0.00	-0.01*	0.00	-0.01	0.13	0.15*	0.23*	0.18*	0.16*
Castor Seed	0.00	0.03	-0.09	0.26	-0.03	-0.15	-0.01	0.02*	0.00	0.00	0.00	0.03	0.00	0.03	0.01	-0.01
Guar Seed	0.00	-0.02$	0.02	-0.01	0.02$	-0.01	-0.01	0.01	0.00	0.00	0.00	0.02	-0.01	0.00	-0.01	-0.01
Gold	0.02	-0.02	-0.01	-0.01	-0.01	-0.02	0.02	-0.04*	-0.03#	-0.05*	-0.05*	-0.04	0.05	0.06	0.12*	0.07#
Silver	-0.07#	-0.04	0.00	-0.05	-0.02	0.11	-0.02	0.03*	0.00	-0.02#	-0.05*	0.00	-0.08#	-0.05	-0.01	0.04
Aluminium	-0.05#	-0.07	0.09	-0.10	0.01	0.01	-0.12*	-0.04*	0.00	-0.05*	-0.07*	0.03	0.04	-0.04	0.09*	0.15*
Copper	-0.01	-0.08	0.09	-0.03	0.01	0.08	-0.10*	-0.06*	-0.06*	-0.05*	-0.02	0.14*	0.13*	0.14*	0.19*	0.10#
Zinc	0.03	-0.21	0.25	-0.09	0.12	-0.17	-0.15*	-0.09*	-0.09*	-0.08*	-0.04$	0.19*	0.12#	0.14*	0.16*	0.14*
Crude Oil	-0.03	0.01	-0.32	0.09	-0.18	0.49	-0.22*	-0.17*	-0.10*	-0.08*	-0.11*	0.28*	0.30*	0.20*	0.17*	0.27*
Natural Gas	-0.01	-0.45*	0.55*	-0.09	-0.22	0.22	-0.02	-0.11*	-0.02	-0.04*	-0.07*	0.04	0.21*	-0.03	0.11*	0.10*

*, #, $ significant at 1, 5 and 10% level respectively

Table 3 (a): Variance Decomposition for Next To Near Month Futures

A. Volatility Explained By Volatility

	Close-to-close Volatility					Close-to-0pen Volatility					Open-to-close Volatility				
	1	5	10	15	20	1	5	10	15	20	1	5	10	15	20
Soy Bean	100%	97%	97%	97%	97%	100%	100%	100%	100%	100%	100%	98%	98%	98%	98%
Maize	100%	86%	78%	77%	76%	100%	94%	88%	87%	87%	100%	100%	99%	99%	99%
Castor Seed	100%	75%	70%	68%	67%	100%	99%	97%	96%	96%	100%	99%	98%	98%	98%
Guar Seed	100%	63%	59%	57%	57%	100%	99%	99%	99%	99%	100%	98%	98%	98%	98%
Gold	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	99%	98%	98%	98%
Silver	100%	100%	99%	99%	99%	100%	100%	100%	100%	100%	100%	100%	99%	99%	99%
Aluminium	100%	97%	97%	98%	98%	100%	99%	97%	95%	95%	100%	98%	98%	98%	98%
Copper	100%	97%	97%	97%	97%	100%	100%	99%	99%	99%	100%	100%	100%	100%	100%
Zinc	100%	93%	94%	94%	94%	100%	99%	99%	99%	99%	100%	100%	99%	99%	99%
Crude Oil	100%	96%	96%	96%	96%	100%	100%	100%	100%	100%	100%	98%	97%	97%	97%
Natural Gas						100%	98%	97%	97%	96%	100%	98%	97%	97%	97%

B. Volatility Explained By Volume

	Close-to-close Volatility					Close-to-0pen Volatility					Open-to-close Volatility				
	1	5	10	15	20	1	5	10	15	20	1	5	10	15	20
Soy Bean	0%	2%	2%	2%	2%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Maize	0%	14%	22%	23%	24%	0%	6%	12%	12%	12%	0%	0%	1%	1%	1%
Castor Seed	0%	25%	30%	31%	32%	0%	1%	2%	3%	3%	0%	0%	0%	0%	0%
Guar Seed	0%	35%	40%	41%	41%	0%	0%	0%	0%	0%	0%	2%	2%	2%	2%
Gold	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Silver	0%	0%	0%	1%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Aluminium	0%	2%	2%	1%	1%	0%	0%	1%	1%	2%	0%	1%	1%	1%	1%
Copper	0%	2%	1%	1%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Zinc	0%	3%	2%	2%	2%	0%	1%	1%	1%	1%	0%	0%	0%	0%	0%
Crude Oil	0%	2%	2%	3%	3%	0%	0%	0%	0%	0%	0%	0%	1%	1%	1%
Natural Gas						0%	2%	3%	3%	3%	0%	1%	0%	0%	0%

C. Volatility Explained By Open Interest

	Close-to-close Volatility					Close-to-0pen Volatility					Open-to-close Volatility				
	1	5	10	15	20	1	5	10	15	20	1	5	10	15	20
Soy Bean	0%	1%	1%	1%	2%	0%	0%	0%	0%	0%	0%	1%	2%	2%	2%
Maize	0%	0%	0%	0%	0%	0%	0%	0%	0%	1%	0%	0%	0%	0%	0%
Castor Seed	0%	0%	1%	1%	1%	0%	0%	1%	1%	1%	0%	1%	1%	1%	2%
Guar Seed	0%	2%	2%	2%	2%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Gold	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	1%	1%	1%	1%
Silver	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	1%	1%	1%
Aluminium	0%	0%	1%	1%	1%	0%	1%	3%	3%	4%	0%	1%	1%	1%	1%
Copper	0%	1%	1%	2%	2%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Zinc	0%	4%	4%	4%	4%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Crude Oil	0%	2%	2%	2%	2%	0%	0%	0%	0%	0%	0%	2%	2%	1%	1%
Natural Gas						0%	0%	0%	0%	0%	0%	1%	2%	2%	2%

Table 3 (b): Variance Decomposition for Next To Near Month Futures

A. Volume Explained By Volatility

	Close-to-close Volatility					Close-to-0pen Volatility					Open-to-close Volatility				
	1	5	10	15	20	1	5	10	15	20	1	5	10	15	20
Soy Bean	0%	3%	4%	4%	4%	4%	4%	3%	2%	2%	0%	0%	0%	0%	0%
Maize	0%	1%	1%	2%	3%	4%	5%	5%	5%	5%	0%	0%	0%	0%	0%
Castor Seed	1%	1%	2%	2%	2%	20%	20%	20%	20%	20%	0%	0%	0%	0%	0%
Guar Seed	1%	3%	3%	3%	3%	22%	22%	22%	22%	22%	0%	5%	5%	5%	5%
Gold	0%	0%	0%	0%	0%	1%	1%	1%	1%	1%	0%	0%	0%	0%	0%
Silver	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Aluminium	1%	2%	2%	2%	2%	2%	2%	2%	2%	2%	0%	0%	0%	0%	0%
Copper	0%	0%	0%	0%	0%	1%	1%	1%	1%	1%	0%	0%	0%	0%	0%
Zinc	1%	1%	1%	1%	1%	1%	2%	2%	2%	2%	0%	0%	0%	0%	0%
Crude Oil	0%	1%	1%	1%	1%	3%	4%	4%	4%	4%	0%	0%	0%	1%	1%
Natural Gas						6%	8%	8%	8%	8%	0%	0%	0%	0%	0%

B. Volume Explained By Volume

	Close-to-close Volatility					Close-to-0pen Volatility					Open-to-close Volatility				
	1	5	10	15	20	1	5	10	15	20	1	5	10	15	20
Soy Bean	100%	97%	96%	96%	96%	96%	96%	97%	98%	98%	100%	99%	99%	99%	99%
Maize	94%	93%	93%	93%	92%	96%	95%	95%	95%	95%	100%	99%	99%	99%	99%
Castor Seed	99%	96%	96%	96%	96%	80%	77%	77%	77%	77%	100%	97%	97%	97%	97%
Guar Seed	99%	94%	94%	94%	94%	78%	75%	75%	75%	75%	100%	92%	92%	92%	92%
Gold	100%	89%	89%	89%	89%	99%	89%	88%	88%	88%	100%	89%	89%	89%	89%
Silver	100%	91%	90%	90%	90%	100%	90%	90%	90%	90%	100%	91%	90%	90%	90%
Aluminium	99%	95%	94%	94%	94%	98%	95%	94%	94%	94%	100%	96%	96%	96%	96%
Copper	100%	88%	87%	87%	87%	99%	87%	87%	87%	87%	100%	88%	88%	87%	87%
Zinc	99%	91%	90%	90%	90%	99%	90%	89%	89%	89%	100%	92%	91%	91%	91%
Crude Oil	100%	90%	89%	89%	89%	97%	88%	87%	87%	87%	100%	91%	90%	90%	90%
Natural Gas						94%	87%	87%	87%	87%	100%	90%	90%	90%	90%

C. Volume Explained By Open Interest

	Close-to-close Volatility					Close-to-0pen Volatility					Open-to-close Volatility				
	1	5	10	15	20	1	5	10	15	20	1	5	10	15	20
Soy Bean	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Maize	6%	6%	5%	5%	5%	0%	0%	0%	0%	0%	0%	0%	0%	1%	1%
Castor Seed	0%	3%	3%	3%	3%	0%	3%	3%	3%	3%	0%	2%	3%	3%	3%
Guar Seed	0%	3%	3%	3%	3%	0%	3%	3%	3%	3%	0%	4%	4%	4%	4%
Gold	0%	11%	11%	11%	11%	0%	11%	11%	11%	11%	0%	11%	11%	11%	11%
Silver	0%	9%	10%	10%	10%	0%	9%	10%	10%	10%	0%	9%	10%	10%	10%
Aluminium	0%	4%	4%	4%	4%	0%	3%	3%	3%	3%	0%	3%	4%	4%	4%
Copper	0%	12%	12%	12%	12%	0%	12%	12%	12%	12%	0%	12%	12%	12%	12%
Zinc	0%	8%	9%	9%	9%	0%	8%	9%	9%	9%	0%	8%	8%	8%	8%
Crude Oil	0%	9%	10%	10%	10%	0%	8%	9%	9%	9%	0%	9%	10%	10%	10%
Natural Gas						0%	5%	5%	5%	5%	0%	9%	10%	10%	10%

Table 3 (c): Variance Decomposition for Next To Near Month Futures

A. Open Interest Explained By Volatility

	Close-to-close Volatility					Close-to-0pen Volatility					Open-to-close Volatility				
	1	5	10	15	20	1	5	10	15	20	1	5	10	15	20
Soy Bean	0%	0%	0%	0%	0%	2%	2%	2%	2%	2%	0%	0%	0%	0%	0%
Maize	0%	1%	1%	2%	3%	0%	2%	2%	2%	3%	0%	2%	2%	2%	2%
Castor Seed	0%	1%	1%	1%	1%	1%	2%	2%	2%	2%	0%	0%	0%	0%	0%
Guar Seed	0%	0%	0%	0%	0%	0%	1%	1%	1%	1%	1%	1%	1%	1%	1%
Gold	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Silver	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Aluminium	2%	3%	3%	3%	3%	0%	0%	1%	1%	1%	0%	0%	0%	0%	0%
Copper	0%	1%	1%	1%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Zinc	1%	1%	1%	1%	2%	0%	1%	1%	1%	1%	0%	0%	0%	0%	0%
Crude Oil	0%	1%	1%	1%	1%	0%	1%	1%	1%	1%	0%	0%	0%	0%	0%
Natural Gas						1%	2%	2%	2%	2%	0%	1%	1%	1%	1%

B. Open Interest Explained By Volume

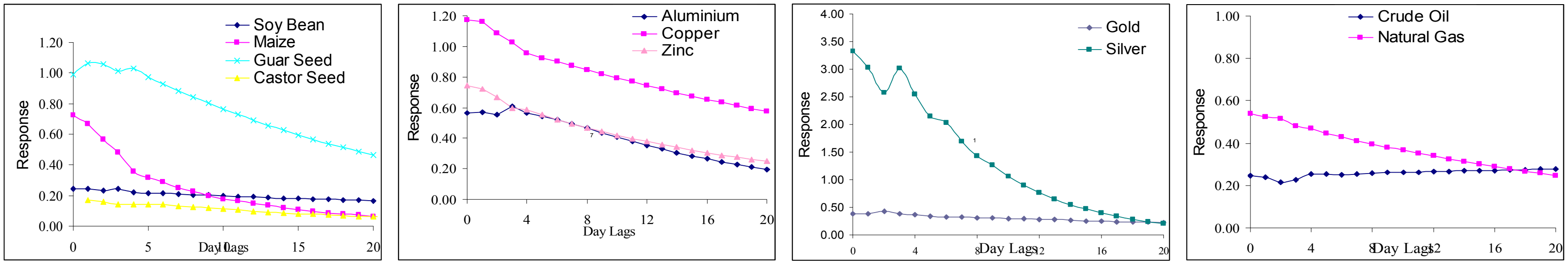
	Close-to-close Volatility					Close-to-0pen Volatility					Open-to-close Volatility				
	1	5	10	15	20	1	5	10	15	20	1	5	10	15	20
Soy Bean	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Maize	6%	6%	5%	5%	5%	5%	5%	4%	4%	4%	6%	6%	5%	5%	4%
Castor Seed	7%	8%	8%	8%	8%	6%	7%	7%	7%	7%	7%	8%	8%	8%	8%
Guar Seed	6%	7%	7%	7%	7%	9%	10%	10%	10%	10%	6%	6%	6%	6%	6%
Gold	29%	30%	31%	31%	31%	29%	30%	31%	31%	31%	29%	30%	31%	31%	31%
Silver	28%	29%	31%	31%	31%	28%	29%	31%	31%	31%	28%	29%	31%	31%	31%
Aluminium	10%	18%	19%	19%	19%	10%	19%	20%	20%	20%	11%	18%	20%	20%	20%
Copper	41%	44%	44%	44%	44%	42%	45%	45%	45%	45%	41%	45%	44%	44%	44%
Zinc	48%	50%	50%	50%	50%	50%	51%	51%	51%	51%	49%	51%	51%	51%	51%
Crude Oil	67%	67%	66%	66%	66%	67%	66%	65%	65%	65%	67%	67%	66%	66%	66%
Natural Gas						43%	43%	44%	44%	44%	40%	40%	40%	40%	40%

C. Open Interest Explained By Open Interest

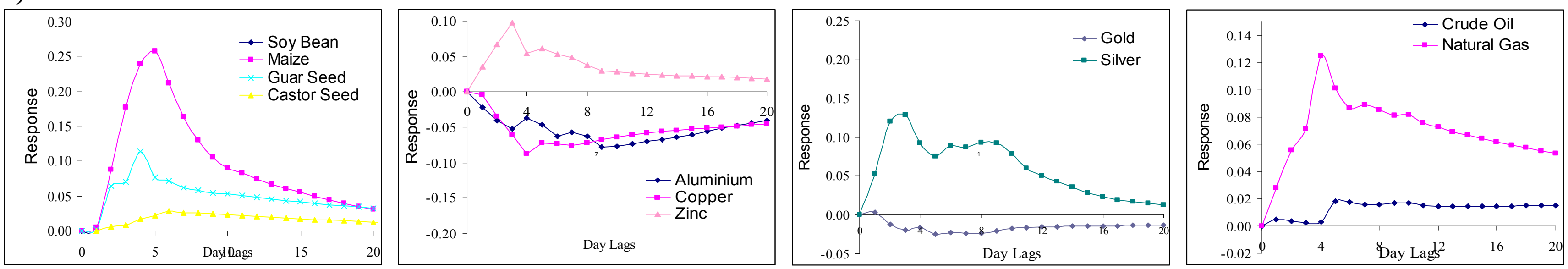
	Close-to-close Volatility					Close-to-0pen Volatility					Open-to-close Volatility				
	1	5	10	15	20	1	5	10	15	20	1	5	10	15	20
Soy Bean	100%	99%	99%	99%	99%	98%	97%	97%	97%	97%	100%	100%	99%	99%	99%
Maize	94%	93%	93%	93%	92%	94%	93%	94%	94%	93%	94%	92%	93%	94%	94%
Castor Seed	93%	91%	91%	91%	91%	93%	91%	91%	91%	91%	93%	92%	92%	92%	92%
Guar Seed	94%	93%	93%	93%	93%	90%	90%	90%	90%	90%	93%	92%	92%	92%	92%
Gold	71%	70%	69%	69%	69%	71%	69%	69%	69%	69%	71%	70%	69%	69%	69%
Silver	72%	71%	69%	69%	69%	72%	71%	69%	69%	69%	72%	71%	69%	69%	69%
Aluminium	88%	79%	78%	78%	78%	90%	81%	79%	79%	79%	89%	82%	80%	80%	80%
Copper	59%	55%	55%	55%	55%	58%	55%	55%	55%	55%	59%	55%	55%	55%	55%
Zinc	51%	48%	49%	49%	49%	50%	48%	48%	48%	48%	51%	49%	49%	49%	49%
Crude Oil	33%	33%	34%	34%	34%	33%	33%	34%	34%	34%	33%	33%	34%	34%	34%
Natural Gas						55%	54%	54%	54%	54%	60%	59%	59%	59%	59%

Figure 1 (a) Impulse Response Function for Commodity Futures Close-To-Open Volatility Response to Shock in Volatility, b) Volume And c) Open Interest in Next To Near Futures.

a) Volatility



b) Volume



C) Open Interest

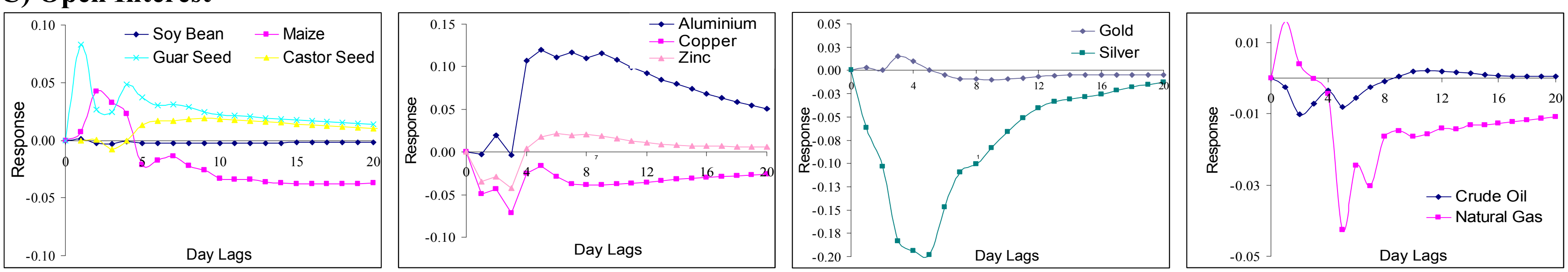
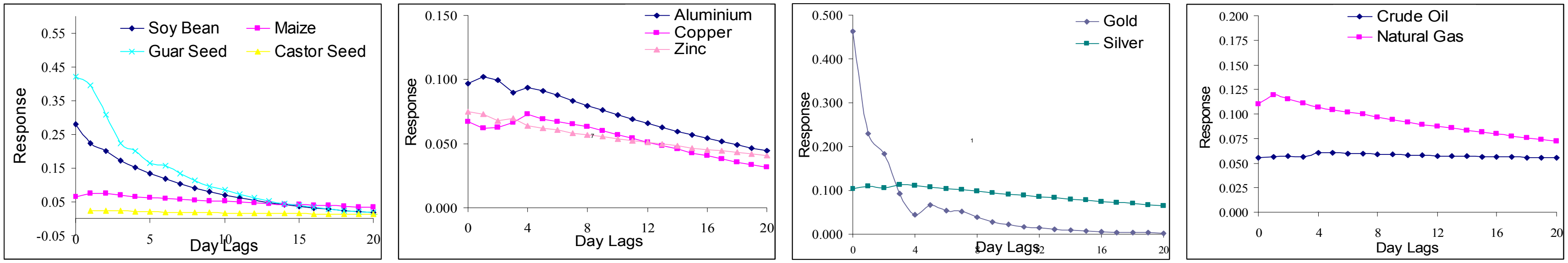
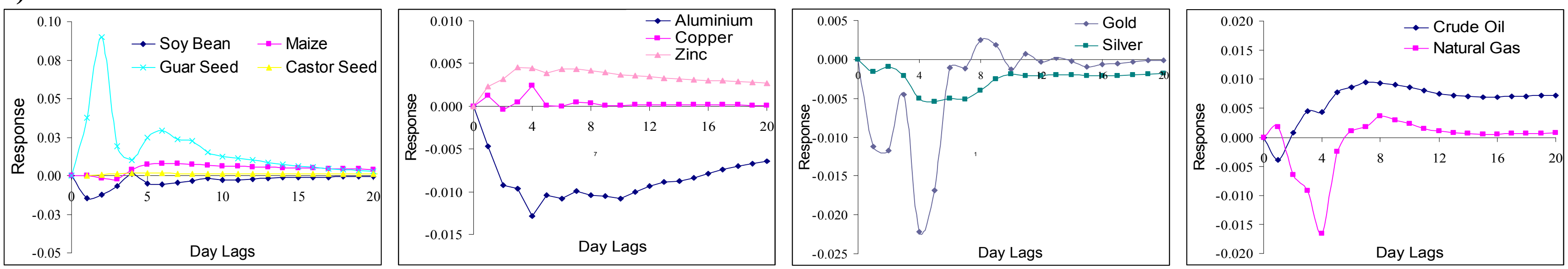


Figure 1 (b) Impulse Response Function for Commodity Futures Open-To-Close Volatility Response to Shock in a) Volatility, b) Volume And c) Open Interest in Next To Near Futures

a) Volatility



b) Volume



C) Open Interest

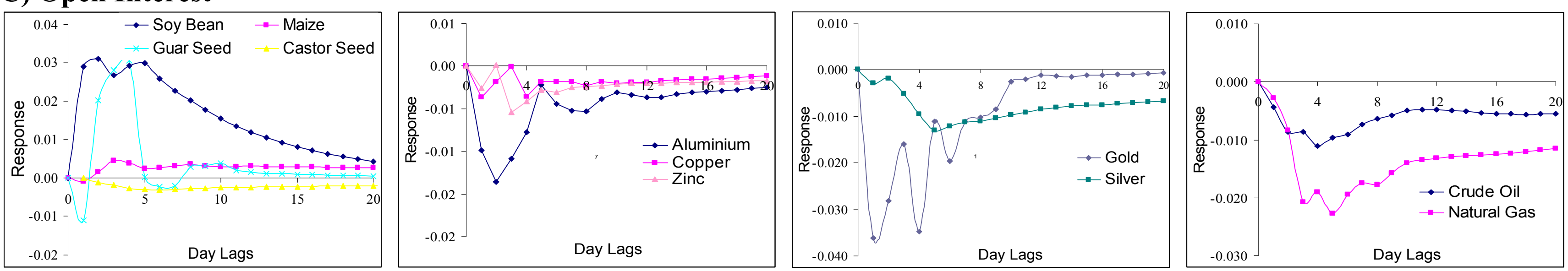
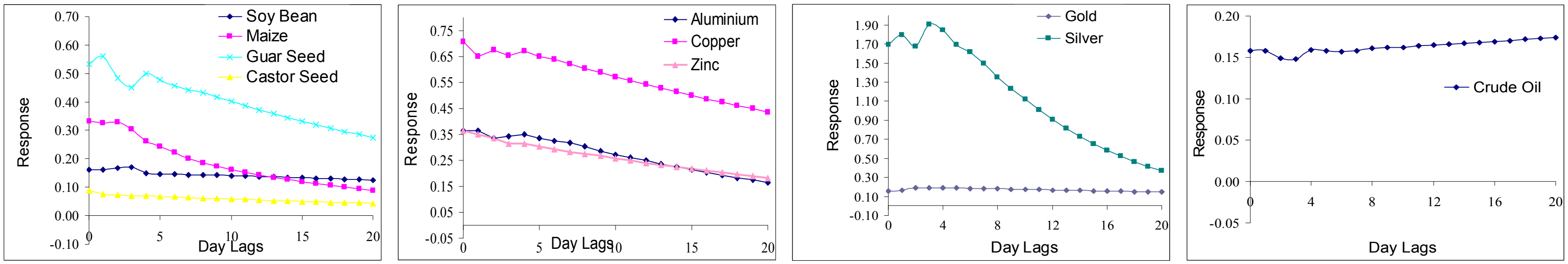
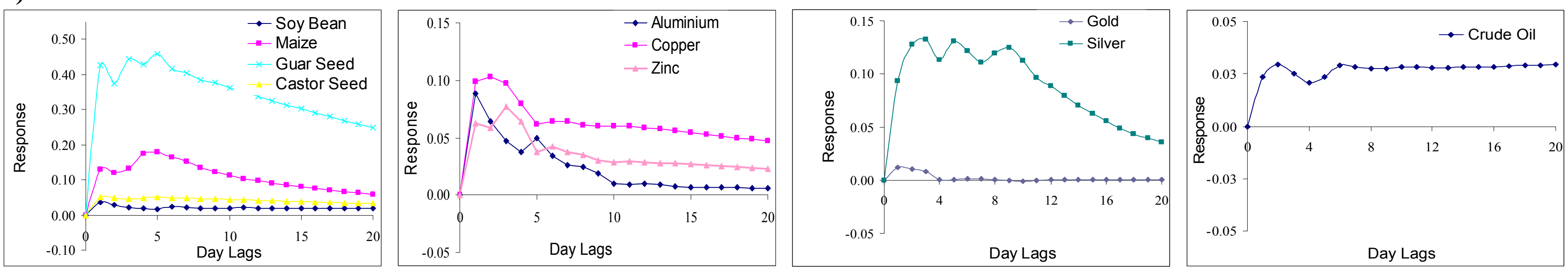


Figure 1 (c) Impulse Response Function for Commodity Futures Close-To-Close Volatility Response to Shock in a) Volatility, b) Volume and c) Open Interest Shock in Next To Near Futures

a) Volatility



b) Volume



C) Open Interest

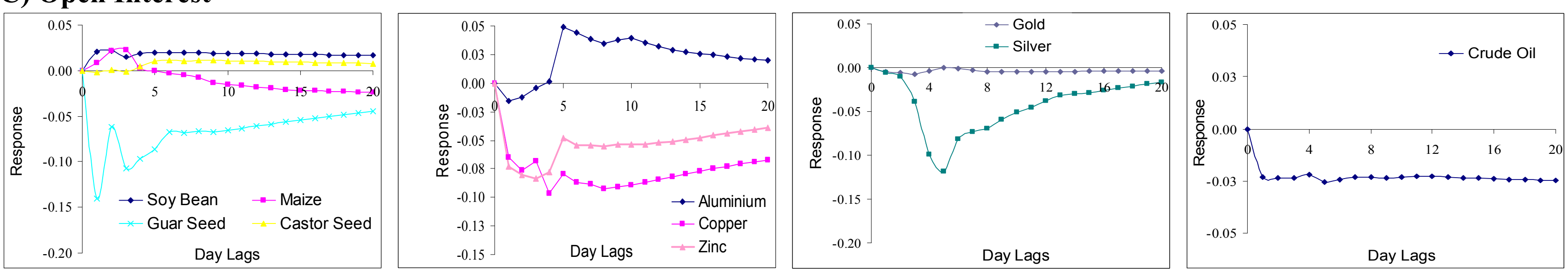
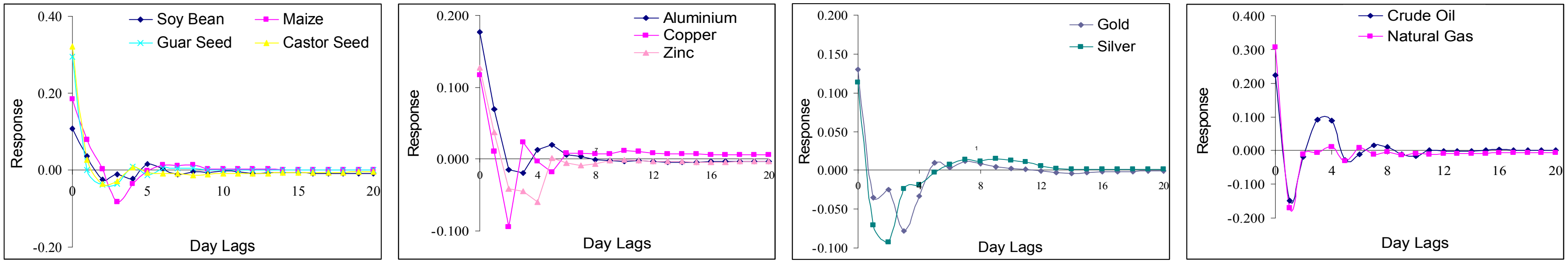
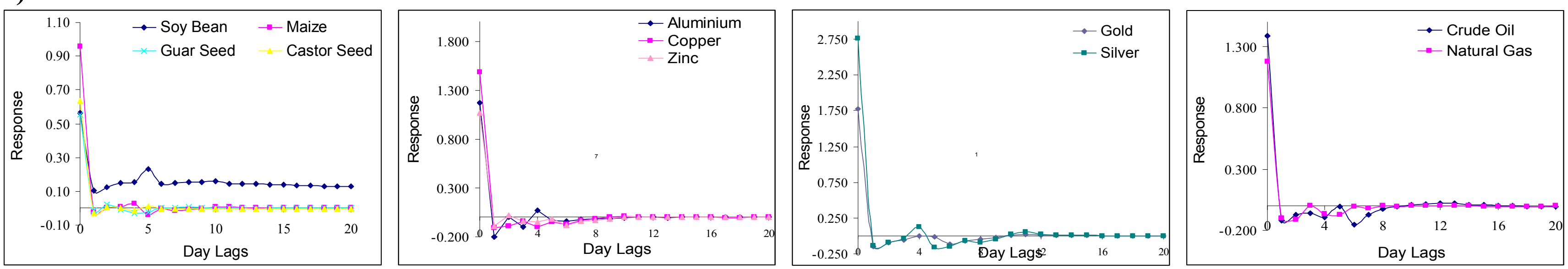


Figure 2 (a) Impulse Response Function for Commodity Futures Volume Response to Shock in a) To Close-To-Open Volatility, b) Volume and c) Open Interest Shock in Next To Near Futures

a) Volatility



b) Volume



c) Open interest

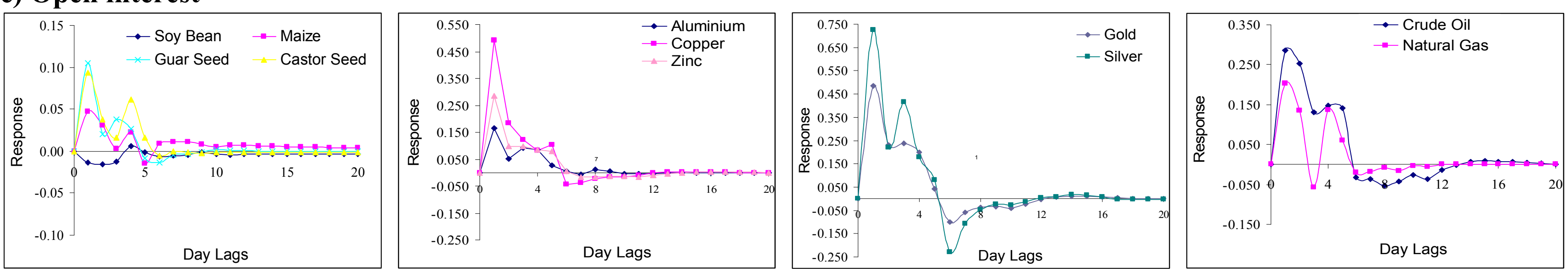


Figure 2 (b) Impulse Response Function for Commodity Futures Volume Response to Shock in a) To Open-To-Close Volatility, b) Volume and c) Open Interest Shock in Next To Near Futures

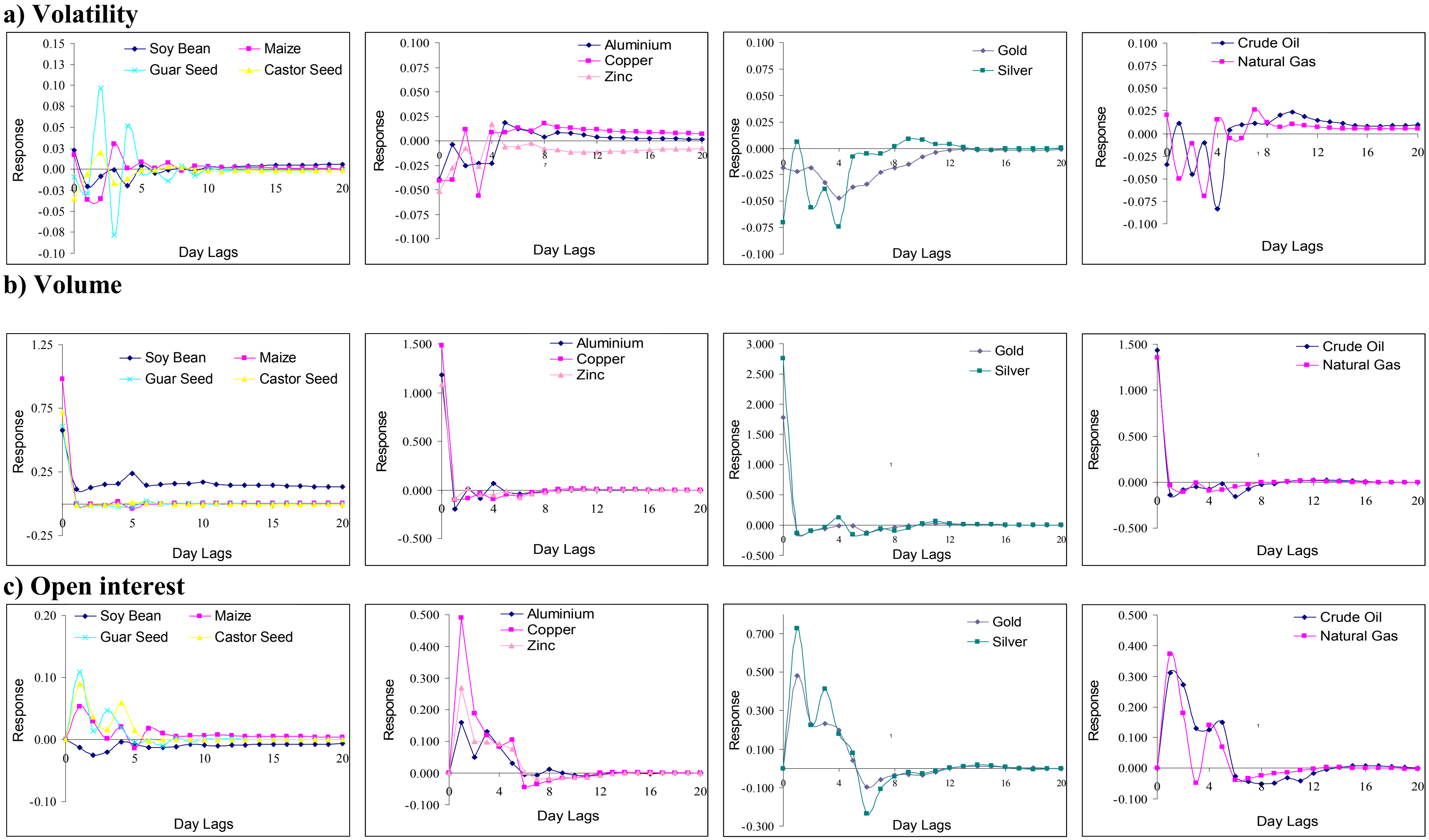
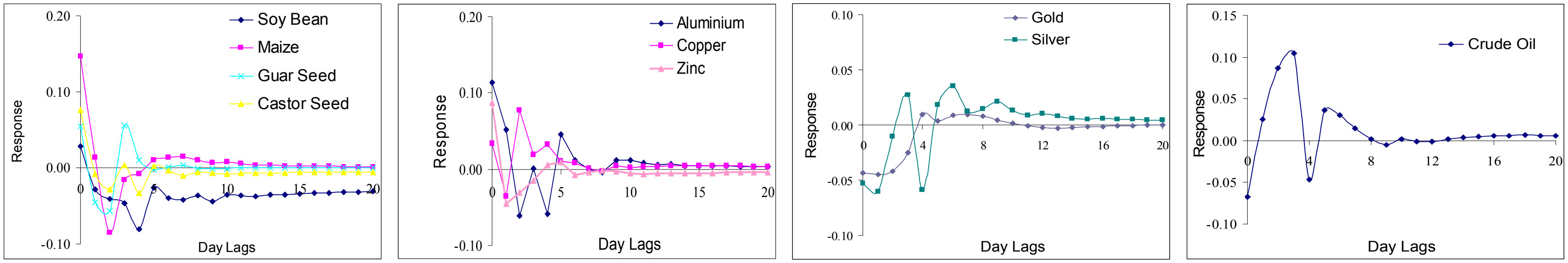
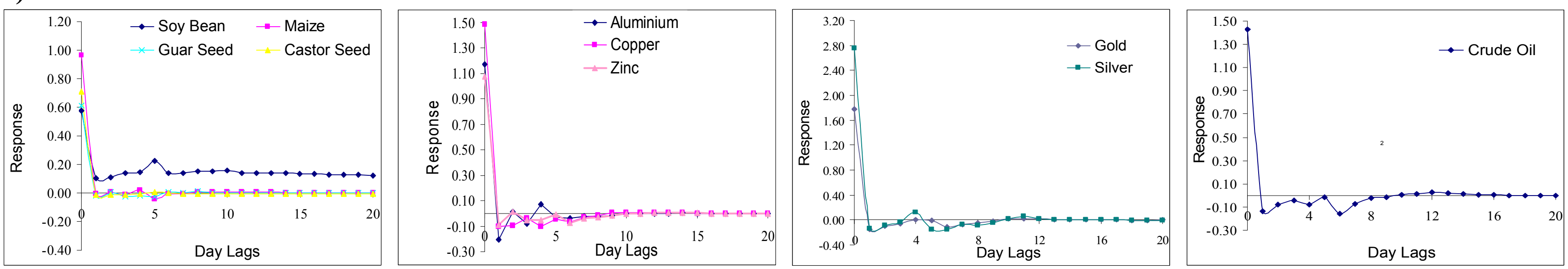


Figure 2 (c) Impulse Response Function for Commodity Futures Volume Response to Shock in a) To Close-To-Close Volatility, b) Volume and c) Open Interest Shock in Next To Near Futures

a) Volatility



b) Volume



c) Open interest

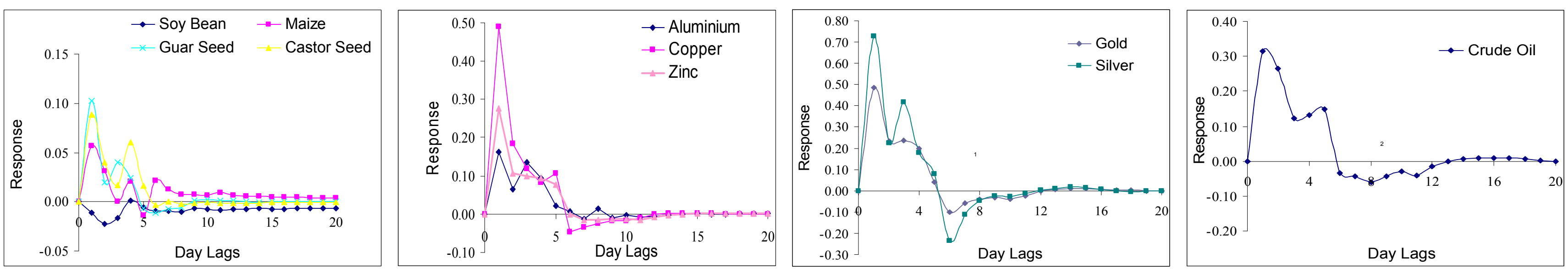
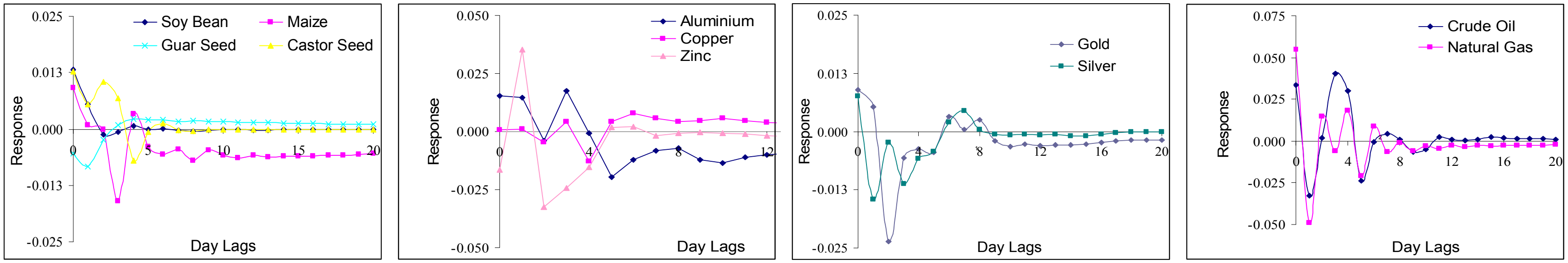
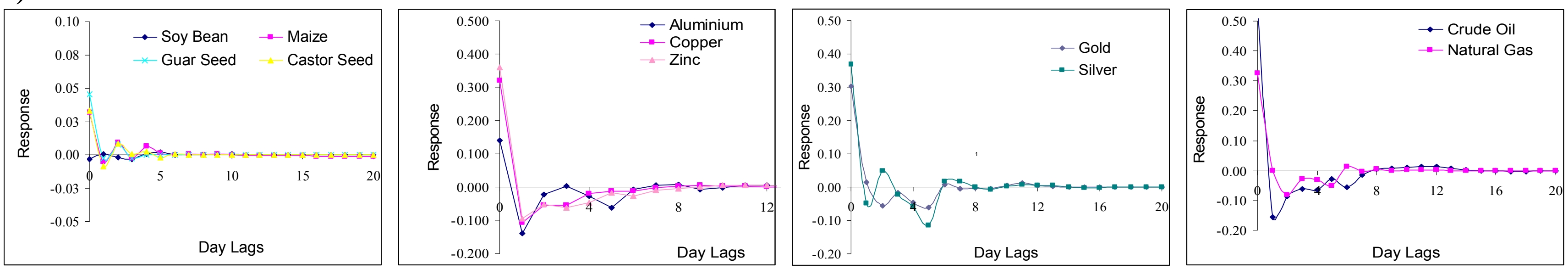


Figure 3 (a) Impulse Response Function for Commodity Futures Open Interest Response to Shock in a) To Close-To-Open Volatility, b) Volume and c) Open Interest Shock in Next To Near Futures

a) Volatility



b) Volume



c) Open interest

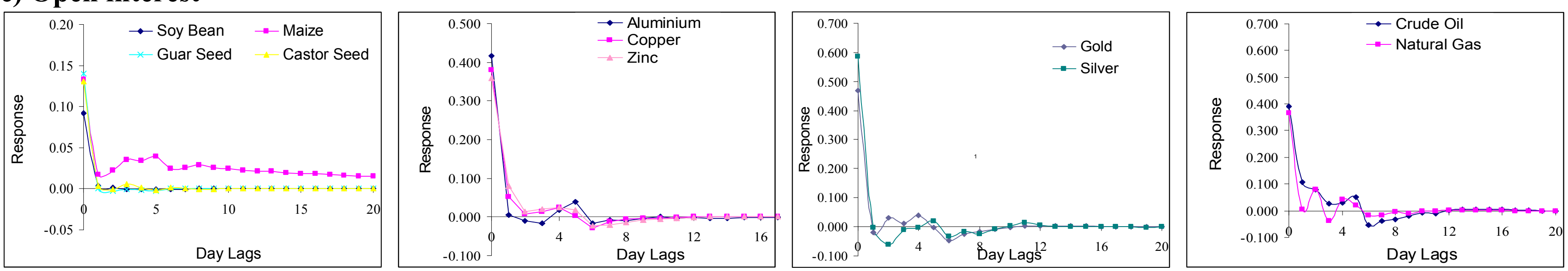
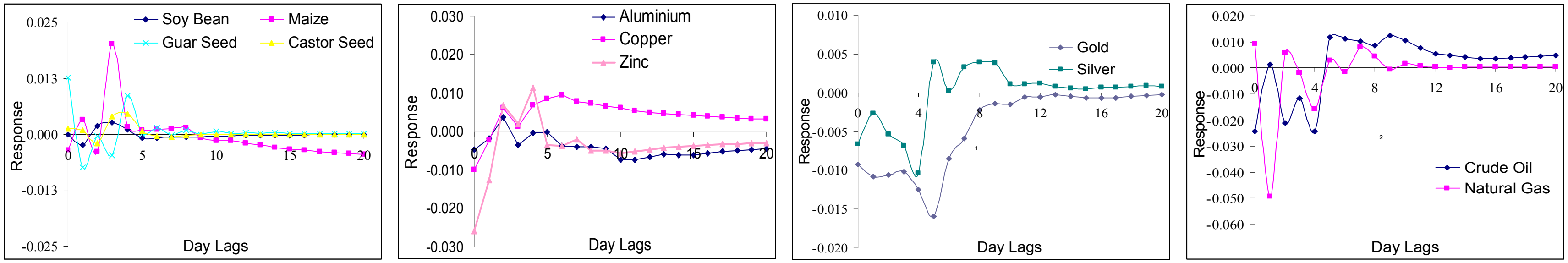
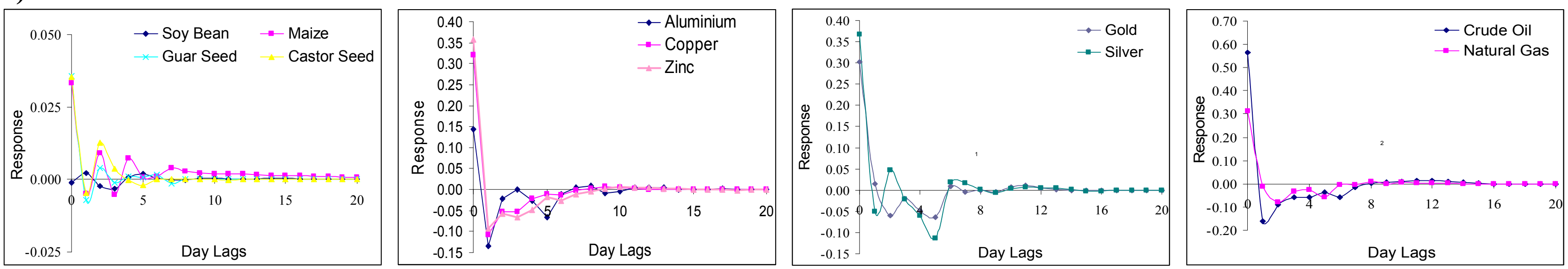


Figure 3 (b) Impulse Response Function for Commodity Futures Open Interest Response to Shock in a) To Open-To-Close Volatility, b) Volume and c) Open Interest Shock in Next To Near Futures

a) Volatility



b) Volume



c) Open interest

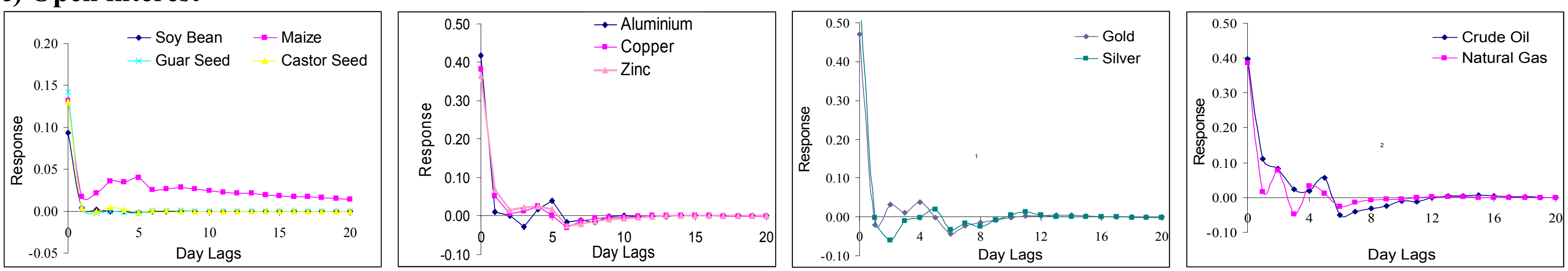
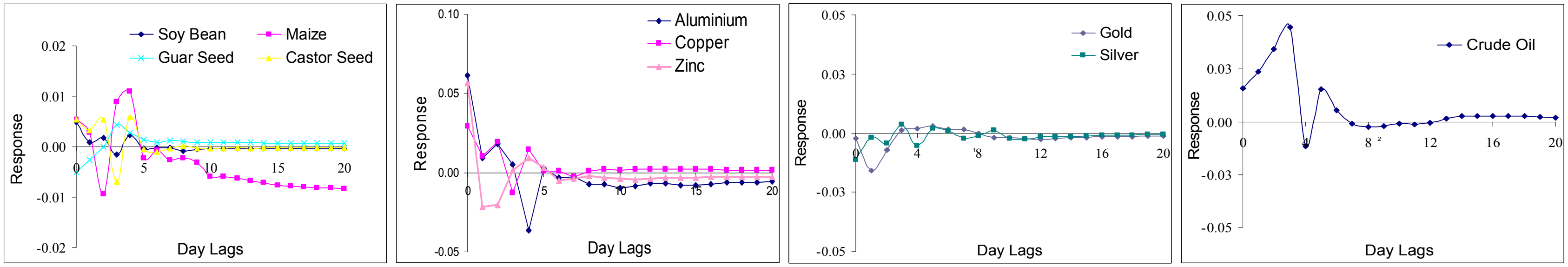
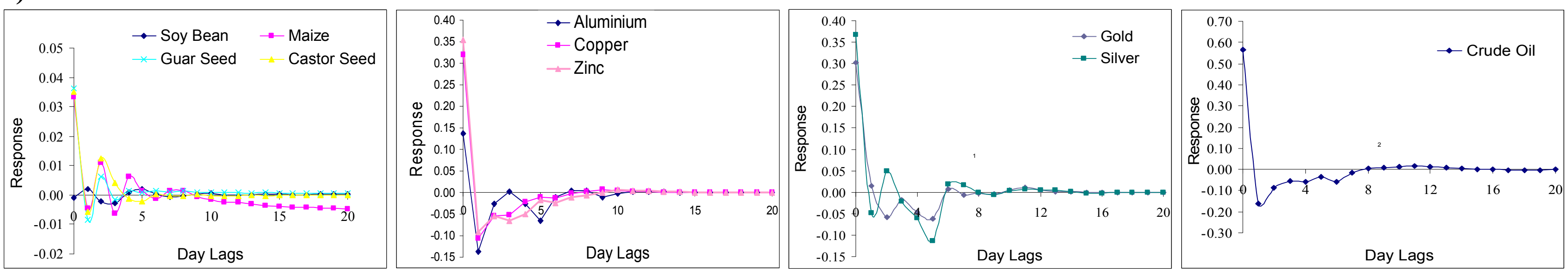


Figure 3 (c) Impulse Response Function for Commodity Futures Open Interest Response to Shock in a) To Close-To-Close Volatility, b) Volume and c) Open Interest Shock in Next To Near Futures

a) Volatility



b) Volume



c) Open Interest