



WHICH STORY MOVES MCX? TESTING THE VALIDITY OF THE MIXTURE OF DISTRIBUTION HYPOTHESIS AND SEQUENTIAL INFORMATION HYPOTHESIS IN THE INDIAN COMMODITY MARKET

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Abstract

This study investigates whether the Mixture of Distribution Hypothesis (MDH) or the Sequential Information Hypothesis (SIH) better explains the relationship between price changes, trading volume, and open interest in Indian commodity futures, thereby assessing market efficiency across base metals, bullion, and energy contracts traded on the Multi Commodity Exchange (MCX). Using daily data for Aluminium, Copper, Lead, Zinc, Gold, Silver, Crude Oil, and Natural Gas spanning 2005–2022, the study applies stationarity tests (ADF, Phillips–Perron, and KPSS), correlation analysis, and VAR-based Granger causality among returns, absolute returns, volume, and open interest. Results show that all transformed series are stationary. Significant positive correlations between absolute returns and both volume and open interest provide broad support for the MDH. Base metals largely exhibit MDH-dominant efficiency with limited linear causality, while bullion and natural gas display SIH-consistent bidirectional or unidirectional causality. Crude oil shows MDH-type independence in causality tests, whereas silver and natural gas reveal speculative, volume-led volatility. The analysis, limited to daily MCX non-agricultural data and linear causality, highlights the need for nonlinear and high-frequency extensions. Findings aid traders and regulators in interpreting volume–volatility co-movements and information flow for improved hedging and risk management.

Keywords: *Mixture of Distribution Hypothesis (MDH); Sequential Information Hypothesis (SIH); Open Interest; Market Efficiency; Commodity Futures; MCX; Volume–Volatility Relationship.*

JEL Classification: G14, G13, C32, C58, G12.

1. Introduction

The relationship between price changes and trading volume is a cornerstone of financial market analysis. Researchers have long sought to understand the dynamics that link information arrival, trading activity, and price formation. Two competing theoretical frameworks dominate this literature: the Mixture of Distribution Hypothesis (MDH) and the Sequential Information Hypothesis (SIH).

The MDH, associated with Clark (1973), Epps and Epps (1976), Tauchen and Pitts (1983), and Harris (1986), posits that the joint distribution of volume and volatility is bivariate normal conditional on a latent mixing variable—typically the rate of information arrival. Under MDH, all traders receive new price signals simultaneously; consequently, volume and absolute price changes should be contemporaneously correlated, but neither variable should Granger-cause the other. In contrast, the SIH (Copeland, 1976; Jennings, Starks, & Fellingham, 1981) assumes that information reaches traders sequentially and randomly. Starting from an initial equilibrium, successive arrival of news causes traders to revise expectations in stages, generating a temporal sequence in which volume can predict subsequent volatility and vice versa. Causality between volume and absolute returns is therefore expected under SIH.

In futures markets, open interest provides an additional dimension of trading activity. It has been interpreted as a proxy for hedging demand (Chen et al., 1995), market depth (Bessembinder & Seguin,



1993), and differences of opinion among traders (Bessembinder et al., 1996). Examining the joint behaviour of returns, absolute returns, volume, and open interest therefore offers a richer test of how information is incorporated into prices.

The Indian commodity market presents a particularly interesting setting. The Multi Commodity Exchange (MCX) accounts for approximately 94 percent of India's commodity derivatives turnover and has matured considerably since its inception in 2003. Understanding whether MDH or SIH better characterises price–volume–open-interest dynamics on MCX has direct implications for technical analysis, hedging effectiveness, and regulatory surveillance. The presence of causality from volume to returns would imply that past trading activity contains predictive information, challenging weak-form efficiency; the absence of such causality, combined with strong contemporaneous correlations, would support a more efficient MDH-type information process.

This study tests the validity of MDH and SIH across eight major non-agricultural commodities traded on MCX—four base metals (Aluminium, Copper, Lead, Zinc), two bullion (Gold, Silver), and two energy contracts (Crude Oil, Natural Gas)—using daily data from 2005 to 2022. By combining correlation analysis with Granger causality tests within a VAR framework, the paper provides empirical evidence on market efficiency and information flow in an important emerging-market commodity exchange.

2. Literature Review

A substantial body of research documents a positive relationship between return volatility and trading volume. The MDH attributes this correlation to joint dependence on a common information-arrival process, while the SIH emphasises sequential dissemination of news. Gallant, Rossi, and Tauchen (1992) employed a semi-nonparametric approach and confirmed that volatility is positively related to volume and that high volume tends to follow large price changes. Tauchen and Pitts (1983) found a positive correlation between the variability of daily price changes and trading volume in the 90-day T-bill futures market. Harris (1986) provided cross-sectional support for MDH, and Lamoureux and Lastrapes (1994) showed that volume helps explain the persistence of stock-return volatility.

Evidence from futures markets is mixed. Grammatikos and Saunders (1986) supported MDH using disaggregated futures data. Bessembinder and Seguin (1993) reported that unexpected volume shocks raise volatility while high open interest dampens it. Fujihara and Mougoué (1997) and Moosa and Silvapulle (2000) highlighted the role of information asymmetry in petroleum and crude-oil futures. McMillan and Speight (2002) found bidirectional causality between volume and volatility, consistent with SIH. Ciner (2002) concluded that volume conveys information about the magnitude but not the direction of price changes in Tokyo commodity futures.

In the Indian context, Kumar and Pandey (2010) observed a positive correlation between volatility and volume in commodity derivatives. Biswas and Rajib (2011) reported evidence consistent with SIH on the basis of Granger causality tests, while Maitra (2014) found that unexpected volume positively affects volatility. Jena (2016) documented a positive volume–return variability link in Nifty index futures. More recent work by Fousekis and Tzaferi (2020) identified nonlinearities in the price–volatility–volume relationship in energy futures, and Go and Lau (2021) reviewed the broader literature on informational efficiency, emphasising market microstructure and behavioural factors.

Despite this accumulated evidence, relatively few studies have jointly examined returns, absolute returns, volume, and open interest across multiple commodity classes on MCX within a unified



MDH–SIH testing framework. The present paper fills this gap by providing a comprehensive empirical assessment for base metals, bullion, and energy futures.

3. Data and Methodology

3.1 Data Description

Daily data for eight commodities were obtained from MCX for the period 2005–2022 (approximately 4,600 trading days). The sample comprises Aluminium, Copper, Lead, Zinc (base metals), Gold and Silver (bullion), and Crude Oil and Natural Gas (energy). These contracts represent the most liquid non-agricultural segments and form the core of MCX's iCOMDEX methodology. Spot prices were collected from the relevant regional markets (Mumbai for industrial metals and energy, Ahmedabad for precious metals). Continuous series were constructed by rolling near-month contracts.

Table 1: Selected Commodities and Sample Periods

Commodity	Futures Market	Spot Market	Sample Period
Aluminium	MCX	Mumbai	8 Nov 2005 – 28 Oct 2022
Copper	MCX	Mumbai	3 Feb 2005 – 25 Oct 2022
Lead	MCX	Mumbai	30 Mar 2006 – 31 Oct 2022
Zinc	MCX	Mumbai	30 Mar 2006 – 31 Oct 2022
Gold	MCX	Ahmedabad	6 Jun 2005 – 4 Oct 2022
Silver	MCX	Ahmedabad	14 May 2005 – 21 Oct 2022
Crude Oil	MCX	Mumbai	29 Apr 2005 – 26 Oct 2022
Natural Gas	MCX	Hazira	19 Oct 2006 – 24 Oct 2022

Source: Author's compilation from MCX.

3.2 Variable Construction

Daily continuously compounded returns, volume changes, and open-interest changes were computed as:

$$R_t = \ln(P_t / P_{t-1}) \times 100$$

$$\Delta V_t = \ln(V_t / V_{t-1})$$

$$\Delta OI_t = \ln(OI_t / OI_{t-1})$$

Absolute returns $|R_t|$ were used as a proxy for volatility. Logarithmic transformations stabilise variance and remove trends, rendering the series suitable for subsequent stationarity and causality analysis.

3.3 Econometric Methods

3.3.1 Unit Root Tests

Stationarity was assessed using the Augmented Dickey–Fuller (ADF), Phillips–Perron (PP), and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests. The ADF regression takes the form:

$$\Delta Y_t = \alpha + \beta t + \phi Y_{t-1} + \sum_{i=1}^p \delta_i \Delta Y_{t-1} + \varepsilon_t$$

Where: Y_t : the dependent variable

α : the constant term

β : the coefficient on a time trend



ϕ : the coefficient on the lagged dependent variable
 ΔY_{t-1} : the differenced dependent variable at lag i
 δ_i : the coefficient on the ith lagged difference term
 ε_t : the error term at time t

The PP test regression below is the Equation (2)

$$\Delta Y_t = a + \beta_t + pY_{t-1} + u_t$$

Below is the KPSS Equation (3)

$$Y_t = \delta t + r_t + e_t$$

where: δt = deterministic trend,

r_t = random walk

e_t = stationary error

The PP test applies a non-parametric correction for serial correlation and heteroskedasticity, while the KPSS test reverses the null hypothesis (stationarity versus unit root). Consistent inference across the three tests strengthens confidence in the stationarity conclusions required for valid Granger causality testing.

3.3.2 Correlation Analysis

Pearson and Spearman rank correlations were computed between (i) returns and volume changes, (ii) absolute returns and volume changes, and (iii) absolute returns and open-interest changes. Significant positive contemporaneous correlations between absolute returns and volume (or open interest) constitute evidence in favour of MDH.

3.3.3 Granger Causality

Linear Granger causality was examined within a bivariate VAR framework. Lag length was selected using the Akaike Information Criterion. Rejection of the null that lagged values of one variable do not help predict another provides evidence of directional information flow and is interpreted as support for SIH. The absence of causality, combined with significant contemporaneous correlation, is interpreted as support for MDH.

Below is the Equation (4 and 5)

$$S_t = \alpha + \sum_{i=1}^l \alpha_i S_{t-1} + \sum_{j=1}^l \beta_j F_{t-1} + \varepsilon_t$$

$$F_t = \omega + \sum_{i=1}^l \gamma_i F_{t-1} + \sum_{j=1}^l \Theta_j S_{t-1} + \varepsilon_t$$

Where: S_t = Spot prices

F_t = Futures prices

4. Empirical Results

4.1 Stationary

Tables reporting ADF, PP, and KPSS statistics (available in the full empirical appendix) show that the p-values for the ADF and PP tests are essentially zero for all return, volume-change, and open-interest-change series across the eight commodities. KPSS statistics lie below conventional critical values. Consequently, all series used in the subsequent analysis are stationary at levels and may be entered directly into the VAR systems.



4.2 Correlation Analysis

Table 2 summarises the key correlation results. For every commodity, the contemporaneous correlation between absolute returns and volume changes is positive and statistically significant at the 1 percent level under both Pearson and Spearman measures. Correlations between absolute returns and open-interest changes are likewise positive and significant for all contracts except Crude Oil (where the Pearson coefficient is insignificant). In contrast, the correlation between signed returns and volume changes is weak or negative for most base metals and statistically insignificant for several contracts.

Table 2: Correlation Results (Absolute Returns vs. Volume / Open Interest)

	Pearson Correlation	Spearman's rho
ALUMINIUM		
Change in volume and Return	-0.072** (0.00)	-0.001 (.930)
Change in volume and Absolute return	0.224** (0.00)	0.287** (0.00)
Change in Open Interest and Absolute returns	0.165** (0.00)	0.069** (0.00)
COPPER		
Change in volume and Return	-0.017 (0.271)	-0.025 (0.109)
Change in volume and Absolute return	0.214** (0.00)	0.321** (0.00)
Change in Open Interest and Absolute returns	0.102** (0.00)	0.078** (0.00)
LEAD		
Change in volume and Return	-0.045** (0.004)	-0.007 (0.662)
Change in volume and Absolute return	0.243** (0.00)	0.329** (0.00)
Change in Open Interest and Absolute returns	0.097** (0.00)	0.074** (0.00)
ZINC		
Change in volume and Return	-0.087** (0.00)	-0.015 (0.341)
Change in volume and Absolute return	0.234** (0.00)	0.314** (0.00)
Change in Open Interest and Absolute returns	0.172** (0.00)	0.060** (0.00)
GOLD		
Change in volume and Return	0.022 (0.164)	-0.001 (0.928)
Change in volume and Absolute return	0.237** (0.00)	0.294** (0.00)
Change in Open Interest and Absolute returns	0.138** (0.00)	0.043** (0.006)
SILVER		
Change in volume and Return	0.027 (0.091)	-0.01 (0.522)
Change in volume and Absolute return	0.226** (0.00)	0.329** (0.00)
Change in Open Interest and Absolute returns	0.115** (0.00)	0.035* (0.027)
CRUDE OIL		
Change in volume and Return	0.003 (0.866)	-0.075** (0.00)
Change in volume and Absolute return	0.014 (0.388)	0.215** (0.00)
Change in Open Interest and Absolute returns	-0.019 (0.238)	0.089** (0.00)
NATURAL GAS		



	Pearson Correlation	Spearman's rho
Change in volume and Return	0.013 (0.410)	0.063** (0.00)
Change in volume and Absolute return	0.184** (0.00)	0.282** (0.00)
Change in Open Interest and Absolute returns	0.139** (0.00)	0.117** (0.00)

Note: ** significant at 1%; * significant at 5%. |R| = absolute return; ΔV = change in volume; ΔOI = change in open interest.

These contemporaneous positive associations between absolute returns and both volume and open interest constitute strong prima facie support for the Mixture of Distribution Hypothesis across the majority of contracts.

4.3 Granger Causality Results: Table 3 reports selected Granger causality outcomes. For base metals, there is generally no significant causality running from volume changes to signed returns, consistent with MDH. Absolute returns, however, frequently Granger-cause volume and open-interest changes, and in several cases open interest also feeds back into absolute returns. Gold and Silver display clearer bidirectional or volume-to-absolute-return causality, aligning more closely with SIH. Crude Oil shows almost complete independence, reinforcing an MDH interpretation, while Natural Gas exhibits strong volume-to-absolute-return and open-interest-to-absolute-return causality, suggestive of speculative, information-driven dynamics.

Table 3: Summary of Key Granger Causality Findings

	ALUMINIUM		COPPER	
	F-Statistic	Prob.	F-Statistic	Prob.
Δ Volume does not Granger Cause Δ Futures Price	0.01924	0.9809	0.58789	0.5555
Δ Futures Price does not Granger Cause Δ Volume	14.3903	6.00E-07	0.65676	0.5186
Absolute Δ Futures Price does not Granger Cause Δ Volume	5.62112	0.0036	10.8343	2.00E-05
Δ Volume does not Granger Cause Absolute Δ Futures Price	1.41158	0.2439	2.81378	0.0601
Absolute Δ Futures Price does not Granger Cause Δ Open Interest	7.49705	0.0006	6.01956	0.0025
Δ Open Interest does not Granger Cause Absolute Δ Futures Price	11.3863	1.00E-05	6.48891	0.0015
	LEAD		ZINC	
	F-Statistic	Prob.	F-Statistic	Prob.
Δ Volume does not Granger Cause Δ Futures Price	2.9643	0.0517	0.42118	0.6563
Δ Futures Price does not Granger Cause Δ Volume	1.92184	0.1465	2.75936	0.0635
Absolute Δ Futures Price does not Granger Cause Δ Volume	13.7604	1.00E-06	13.599	1.00E-06



Δ Volume does not Granger Cause Absolute Δ Futures Price	3.55765	0.0286	0.02937	0.9711
Absolute Δ Futures Price does not Granger Cause Δ Open Interest	3.49842	0.0303	3.62854	0.0266
Δ Open Interest does not Granger Cause Absolute Δ Futures Price	9.97507	5.00E-05	3.55838	0.0286
	GOLD		SILVER	
	F-Statistic	Prob.	F-Statistic	Prob.
Δ Volume does not Granger Cause Δ Futures Price	0.8001	0.4494	3.41681	0.0329
Δ Futures Price does not Granger Cause Δ Volume	4.47247	0.0115	8.1666	0.0003
Absolute Δ Futures Price does not Granger Cause Δ Volume	16.482	7.00E-08	19.9192	2.00E-09
Δ Volume does not Granger Cause Absolute Δ Futures Price	6.02585	0.0024	8.00617	0.0003
Absolute Δ Futures Price does not Granger Cause Δ Open Interest	2.92258	0.0539	10.0532	4.00E-05
Δ Open Interest does not Granger Cause Absolute Δ Futures Price	10.9876	2.00E-05	24.1359	4.00E-11
	CRUDE OIL		NATURAL GAS	
	F-Statistic	Prob.	F-Statistic	Prob.
Δ Volume does not Granger Cause Δ Futures Price	0.01947	0.9807	1.23899	0.2898
Δ Futures Price does not Granger Cause Δ Volume	0.20083	0.8181	13.5462	1.00E-06
Absolute Δ Futures Price does not Granger Cause Δ Volume	0.14863	0.8619	15.2023	3.00E-07
Δ Volume does not Granger Cause Absolute Δ Futures Price	0.54552	0.5796	3.0497	0.0475
Absolute Δ Futures Price does not Granger Cause Δ Open Interest	0.2047	0.8149	0.10112	0.9038
Δ Open Interest does not Granger Cause Absolute Δ Futures Price	0.20648	0.8135	30.3917	8.00E-14

Note: Arrows indicate statistically significant Granger causality at conventional levels. Full F-statistics and p-values are available in the empirical appendix.

4.4 Evaluation of MDH versus SIH: Table 4 synthesises the evidence. Base metals (Aluminium, Copper, Lead, Zinc) display strong contemporaneous absolute-return–volume correlations together with limited or no volume-to-return causality, supporting an MDH interpretation and implying relatively efficient information incorporation. Gold and Silver exhibit both significant correlations and clear causality patterns, favouring SIH. Crude Oil is closest to pure MDH (contemporaneous correlation under Spearman, virtually no causality). Natural Gas combines MDH-type correlation with strong SIH-type causality, consistent with the presence of speculative activity.



Table 4: Overall Evaluation of MDH versus SIH

Commodity	Based on Correlation	Based on Causality
Aluminium	MDH	SIH (partial)
Copper	MDH	SIH (partial)
Lead	MDH	SIH (partial)
Zinc	MDH	SIH (partial)
Gold	SIH / MDH	SIH
Silver	SIH / MDH	SIH
Crude Oil	MDH	MDH
Natural Gas	MDH	SIH

Source: Author's synthesis of correlation and causality results.

Conclusion

This study has tested the Mixture of Distribution Hypothesis and the Sequential Information Hypothesis in the Indian commodity futures market using daily data on eight major MCX contracts from 2005 to 2022. After confirming stationarity of all transformed series, the analysis combined contemporaneous correlation measures with linear Granger causality tests among returns, absolute returns, volume, and open interest.

Three broad conclusions emerge. First, absolute returns are positively and significantly correlated with both volume and open-interest changes across virtually all commodities, providing consistent support for the MDH's prediction of joint dependence on a common information-arrival process. Second, linear causality patterns differ systematically by commodity class. Base metals display limited volume-to-return causality and are therefore closer to the MDH ideal of simultaneous information incorporation and higher market efficiency. Bullion (especially Silver) and Natural Gas exhibit clearer bidirectional or volume-led causality, consistent with SIH and suggestive of sequential information arrival or speculative activity. Crude Oil is the purest MDH case, showing almost no causal linkages. Third, open interest frequently participates in the causal network, confirming its informational relevance beyond simple volume.

These findings carry practical implications. Traders and risk managers can interpret strong contemporaneous volume–volatility co-movements as evidence of information-driven rather than purely noisy trading, while remaining alert to causal volume effects in Silver and Natural Gas that may signal speculative pressure. Regulators may use the differential efficiency rankings to prioritise surveillance resources toward contracts that display SIH-type sequential dynamics. From a research perspective, the results underscore the value of examining both correlation and causality, and of distinguishing among commodity classes rather than treating the market as homogeneous.

Several limitations should be noted. The analysis relies on daily data and linear Granger tests; nonlinear causality, high-frequency microstructure effects, and time-varying relationships remain unexplored. Agricultural commodities traded on NCDEX were excluded and merit separate investigation. Future work could usefully incorporate GARCH-type volatility models, nonparametric causality tests, and wavelet-based multi-scale analysis to refine the present conclusions. In sum, neither MDH nor SIH provides a universal description of MCX non-agricultural futures. Base metals



and crude oil lean toward MDH-style efficiency, while bullion and natural gas reveal sequential information flows. Recognising this heterogeneity is essential for accurate modelling of information transmission, effective hedging, and informed regulatory design in India's commodity derivatives market.

6. Key Suggestions

The principal practical and policy implications of the study may be summarised as follows:

- **Risk management and hedging:** Where MDH holds, distinct futures–spot price patterns call for robust, dynamic hedging strategies. Under SIH, timely monitoring of information releases becomes critical.
- **Market surveillance:** Contracts exhibiting SIH-type causality (Silver, Natural Gas) warrant closer regulatory attention to detect potential manipulation or excessive speculation.
- **Liquidity and infrastructure:** Enhancing market depth supports efficient price discovery under MDH; technological improvements in information dissemination reinforce transparency under SIH.
- **Collaborative research:** Continued partnership among exchanges, regulators, and academic institutions can deepen understanding of information-driven price dynamics and further raise the efficiency of India's commodity markets.

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