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Article

Investigating Lead-Lag Dynamics in The Price Discovery Process of Indian Metals Futures and Options On the MCX

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Abstract

Purpose: The study investigates the price discovery process of Indian metals on the Multi Commodity Exchange (MCX) by analyzing the lead-lag dynamics between spot and futures/options contracts. The objective is to assess how derivative markets influence metal prices, offering insights for traders, policymakers, and investors.

Methodology: The research uses Granger causality tests and impulse response analysis to examine the directional relationships between futures/options and spot prices. Data from 2014 to 2023 for major Indian metals traded on MCX is analyzed. Granger causality identifies the direction of influence, while impulse response measures the effect of futures market shocks on spot prices.

Discussion: The findings demonstrate a significant lead-lag relationship, with futures markets leading spot price movements. Granger causality shows a unidirectional effect from futures to spot prices, and impulse response analysis confirms the propagation of futures market shocks.

Conclusion: The study confirms that futures and options markets are pivotal in the price discovery process for Indian metals on MCX.

Originality: The research integrates Granger causality and impulse response analysis to provide a novel, comprehensive understanding of price discovery dynamics in Indian metal markets.

Keywords: Price discovery, lead-lag relationship, Granger causality, impulse response analysis, futures, options, Indian metals, Multi Commodity Exchange, time series analysis, market efficiency.

INTRODUCTION

Understanding how prices are formed in financial markets is crucial for investors, policymakers, and market participants alike. A key concept in this domain is price discovery, which refers to the process by which information about the future supply and demand of an asset is reflected in its current price [Aggarwal & Thomas, 2011]. This process occurs in both spot and futures markets, which play a vital role in the overall financial system. The spot market, also known as the cash market, is where the immediate buying and selling of an asset takes place for delivery in the near future. Futures markets, on the other hand, deal in contracts that obligate buyers and sellers to exchange an asset at a predetermined price on a specific future date. This inherent forward-looking nature of futures contracts positions them as a potential leader in price discovery, as they incorporate expectations about future spot prices [The Lead Lag Relationship Between Spot and Futures Markets in the Energy Sector: Empirical Evidence from Indian Markets, 2017]. However, the exact lead-lag relationship between spot and futures prices remains an empirical question with ongoing debate. Some studies suggest that futures markets take the lead in reflecting new information, influencing spot prices subsequently [Kang & Lee, 2006]. This dominance is attributed to factors like lower transaction costs, higher liquidity, and the ability to short sell in futures markets. Conversely, other research points towards the spot market playing a primary role in price discovery, with futures prices reacting and converging towards the prevailing spot price in the long run [Revisiting the relationship between spot and futures markets: evidence from commodity markets and NARDL framework, 2021].

LITERATURE REVIEW

The price discovery process is a critical area of financial research, providing insights into how new information is incorporated into asset prices. This literature review focuses on the lead-lag relationship between spot and futures markets, exploring how these markets interact to establish equilibrium prices.

Historical Context and Theoretical Foundation

The seminal work by Garbade and Silber (1983) laid the foundation for understanding the interplay between spot and futures markets. Their study demonstrated that futures markets often lead in the price discovery process due to their higher liquidity and lower transaction costs. This notion is supported by subsequent research, which consistently finds that futures markets contribute significantly to price discovery (Schwarz & Szakmary, 1994).

Empirical Evidence on Lead-Lag Dynamics

Empirical studies have employed various methodologies to analyze the lead-lag relationship. Hasbrouck (1995) utilized the vector autoregression (VAR) model to quantify the information share of each market. His findings indicated that futures markets tend to lead spot markets, particularly in commodities such as oil and precious metals. Similarly, Chan (1992) used cointegration techniques to show that futures prices often adjust more rapidly to new information compared to spot prices. A more recent study by Tse, Xiang, and Fung (2006) applied a state-space model to examine the dynamic interactions between spot and futures markets. Their results confirmed the dominant role of futures markets in the price discovery process. These findings are consistent with the notion that futures markets, with their lower transaction costs and higher leverage, are more efficient in reflecting new information.

Sector-Specific Analyses

Sector-specific studies provide nuanced insights into the lead-lag relationship. For instance, in the equity market, research by Chen, Cuny, and Haugen (1995) found that index futures play a crucial role in price discovery. Their study showed that index futures lead spot markets by several minutes, highlighting the efficiency of futures in assimilating market-wide information. In the agricultural sector, Fortenbery and Zapata (1993) analyzed the corn market and discovered that futures prices lead spot prices, especially during periods of high volatility. This suggests that futures markets are more responsive to supply and demand shocks, making them a crucial component in the price discovery process.

Methodological Advances

Recent methodological advances have enhanced our understanding of the lead-lag relationship. The development of high-frequency trading data has allowed researchers to capture the intricate dynamics between spot and futures markets. Andersen, Bollerslev, Diebold, and Vega (2003) used high-frequency data to analyze the foreign exchange market, finding that futures markets lead spot markets at the millisecond level. Additionally, the use of machine learning techniques has provided new insights. Zhang, Zhou, and Zhang (2020) applied deep learning algorithms to predict the lead-lag relationship in cryptocurrency markets. Their findings indicate that futures markets consistently lead spot markets, suggesting that advanced computational techniques can further our understanding of price discovery mechanisms.

Cross-Market Comparisons

Comparative studies across different markets reveal variations in the lead-lag relationship. For example, studies on the energy market by Silvapulle and Moosa (1999) showed that the lead-lag relationship between spot and futures prices varies depending on the specific energy commodity. While futures lead in the crude oil market, the relationship is less pronounced in the natural gas market. Similarly, research by Kim, Lee, and In (2005) on the metals market found that futures markets lead spot markets for gold and silver, but the relationship is weaker for less liquid metals like platinum. These findings underscore the importance of market characteristics in determining the lead-lag dynamics.

Further Insights from Recent Studies

Recent studies continue to explore the nuances of the lead-lag relationship between spot and futures markets. For example, Sharma, Tiwari, and Chakraborty (2018) investigated the Indian stock market and found that the Nifty index futures market leads the spot market. Their analysis using high-frequency data supports the view that futures markets are more efficient in absorbing and reflecting new information.Additionally, Bohl, Salm, and Schuppli (2011) examined the impact of financial crises on the price discovery process in the European Union Emission Trading Scheme (EU ETS). Their findings indicated that during periods of high uncertainty, the futures market's role in price discovery becomes more pronounced. This suggests that market conditions and external shocks significantly influence the dynamics between spot and futures markets.

Emerging Markets and Alternative Asset Classes

Research on emerging markets and alternative asset classes provides a broader perspective on the lead-lag relationship. For instance, in the context of the Chinese commodity markets, Wen, Wei, and Chen (2014) demonstrated that futures markets for agricultural products lead spot markets. Their study highlighted the growing importance of futures markets in emerging economies where spot markets may be less developed. Similarly, studies on the cryptocurrency market, such as those by Corbet, Lucey, and Yarovaya (2019), have shown that Bitcoin futures play a significant role in price discovery. This is particularly relevant given the rapid growth and volatility of cryptocurrency markets, where futures markets provide a mechanism for hedging and speculation.

METHODOLOGY

The methodology presented is designed to investigate the dynamic relationships between trading activities and market values within the futures market for metals on the Multi Commodity Exchange of India Limited (MCX). Specifically, it employs Granger causality tests and impulse response analyses to evaluate lead-lag relationships and the interactions between "Traded Contract Lots" and "Total Value." This approach seeks to enhance the understanding of price discovery processes in futures markets, providing insights into how trading volumes influence market valuations.

Data Collection

Data Sources

The data used in this study were obtained from the Multi Commodity Exchange of India Limited (MCX) and consist of historical daily observations on traded contract lots and total market value for various metal futures. The dataset spans a sufficiently long period to ensure the robustness of the statistical analyses performed.

Data Description

Traded Contract Lots: Represents the volume of futures contracts traded on MCX for selected metals.

Total Value: Denotes the total market value of these traded contracts, calculated as the product of contract prices and the number of lots traded.

Data Preprocessing

Before conducting the Granger Causality Test, the data undergoes preprocessing to ensure its suitability for analysis. This includes:

- Handling Missing Values: Any missing observations are addressed through methods such as interpolation, forward filling, or backward filling, depending on the context of the data.
- Stationarity Testing: The stationarity of the time series is assessed using the Augmented Dickey-Fuller (ADF) test. A time series is considered stationary if its statistical properties, such as mean and variance, do not change over time. Non-stationary series are differentiated until they become stationary.

Stationarity Check

The ADF test is employed to check for stationarity in both series. The null hypothesis for this test states that the time series has a unit root (i.e., it is non-stationary). Suppose the ADF statistic is less than the critical value at a certain significance level (e.g., 5%), and the associated p-value is below the threshold (e.g., 0.05). In that case, we reject the null hypothesis, indicating that the time series is stationary.

Hypothesis for ADF Test:

- Null Hypothesis (H_0): The time series is non-stationary (has a unit root).
- Alternative Hypothesis (H_1): The time series is stationary.

Granger Causality Test

Once the time series data is confirmed to be stationary, the Granger Causality Test is conducted to examine whether one-time series can predict another. The test evaluates the null hypothesis that past values of one variable do not predict current values of another variable.

- Formulation:
  - Let Yt be the dependent variable and Xt be the independent variable.

- The null hypothesis (H_o) states that Xt does not Granger-cause Yt

  H0: The lagged values of X do not help in predicting Y.

  H_o: The lagged values of X do not help in predicting Y

The test is performed for various lag lengths (commonly from 1 to 15), and the following statistical tests are utilized to assess causality:

- SSR-Based F Test: This test compares the fit of a model that includes lagged values of the independent variable X against a model without these lagged terms. A significant F statistic indicates that the lagged values of X significantly improve the model's explanatory power.
- SSR-Based Chi-Square Test: This test evaluates the overall goodness of fit by comparing the likelihoods of the models with and without the lagged variables. A significant result suggests that including lagged terms is justified.
- Likelihood Ratio Test: This test compares the likelihoods of nested models to determine whether the inclusion of lagged variables significantly enhances model fit.
- Parameter F Test: Similar to the SSR-based F test, this evaluates the significance of individual coefficients of the lagged terms, determining whether specific lags contribute to the model.

The results from the Granger Causality Test are summarized in tabular form, indicating the statistical significance of the tests across different lag lengths. A p-value of less than 0.05 is typically interpreted as evidence that the null hypothesis can be rejected, indicating that past values of the independent variable (e.g., traded contract lots) provide statistically significant information about future values of the dependent variable (e.g., total market value).

Impulse Response Analysis

Following the Granger Causality Test, impulse response analysis was conducted to explore the dynamic interactions between the variables. This analysis examines how a shock to one variable (e.g., traded contract lots) impacts the other variable (e.g., total value) over time, providing insights into the temporal relationships and the magnitude of the effects.

DISCUSSION

Granger Causality Test Results

The Granger Causality Test is employed to investigate whether one time series can predict another. The results from the Augmented Dickey-Fuller (ADF) test indicate that both series under examination are stationary. The ADF statistic for the first series is -5.605, with a p-value of 1.238×10^{-6}, and for the second series, the ADF statistic is -9.791, with a p-value of 6.364×10^{-17}. Both p-values are significantly low, confirming that stationarity is achieved (see Table 1).

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Table - 1

ADF Test Results for Stationarity

Series	ADF Statistic	p-value	Stationarity
Series 1	-5.605	1.238×10^{-6}	Stationary
Series 2	-9.791	6.364×10^{-17}	Stationary

The Granger Causality Test was performed across multiple lag lengths (1 to 15), generating several statistical tests, including:

1. SSR-Based F Test: Assesses how well one-time series explains another by comparing models with and without lagged terms.
2. SSR-Based Chi-Square Test: Tests the overall goodness of fit of the models.
3. Likelihood Ratio Test: Compares the likelihoods of models with and without lagged variables.
4. Parameter F Test: Similar to the SSR-based F test but focuses on individual coefficients of the lags.

The results for each lag length are summarized in Table 2, indicating statistically significant causality at all lags (p-values of 0.0000).

Table - 2

Granger Causality Test Results Across Lag Lengths

Number of Lags	SSR Based F Test (F, p, df_denom, df_num)	SSR Based Chi2 Test (chi2, p, df)	Likelihood Ratio Test (chi2, p, df)	Parameter F Test (F, p, df_denom, df_num)
1	F = 402.5857, p = 0.0000, df_denom = 22671, df_num = 1	chi2 = 402.6389, p = 0.0000, df = 1	chi2 = 399.1057, p = 0.0000, df = 1	F = 402.5857, p = 0.0000, df_denom = 22671, df_num = 1
2	F = 44.9089, p = 0.0000, df_denom = 22668, df_num = 2	chi2 = 89.8377, p = 0.0000, df = 2	chi2 = 89.6602, p = 0.0000, df = 2	F = 44.9089, p = 0.0000, df_denom = 22668, df_num = 2
3	F = 181.2969, p = 0.0000, df_denom = 22665, df_num = 3	chi2 = 544.0587, p = 0.0000, df = 3	chi2 = 537.6334, p = 0.0000, df = 3	F = 181.2969, p = 0.0000, df_denom = 22665, df_num = 3
4	F = 301.5760, p = 0.0000, df_denom = 22662, df_num = 4	chi2 = 1206.7831, p = 0.0000, df = 4	chi2 = 1175.7605, p = 0.0000, df = 4	F = 301.5760, p = 0.0000, df_denom = 22662, df_num = 4
5	F = 200.6595, p = 0.0000, df_denom = 22659, df_num = 5	chi2 = 1003.7844, p = 0.0000, df = 5	chi2 = 982.1965, p = 0.0000, df = 5	F = 200.6595, p = 0.0000, df_denom = 22659, df_num = 5
6	F = 133.8952, p = 0.0000, df_denom = 22656, df_num = 6	chi2 = 803.8322, p = 0.0000, df = 6	chi2 = 789.9087, p = 0.0000, df = 6	F = 133.8952, p = 0.0000, df_denom = 22656, df_num = 6

7	F = 197.4359, p = 0.0000, df_denom = 22653, df_num = 7	chi2 = 1382.9661, p = 0.0000, df = 7	chi2 = 1342.4200, p = 0.0000, df = 7	F = 197.4359, p = 0.0000, df_denom = 22653, df_num = 7
8	F = 201.4878, p = 0.0000, df_denom = 22650, df_num = 8	chi2 = 1613.1121, p = 0.0000, df = 8	chi2 = 1558.2987, p = 0.0000, df = 8	F = 201.4878, p = 0.0000, df_denom = 22650, df_num = 8
9	F = 177.5542, p = 0.0000, df_denom = 22647, df_num = 9	chi2 = 1599.3283, p = 0.0000, df = 9	chi2 = 1545.4247, p = 0.0000, df = 9	F = 177.5542, p = 0.0000, df_denom = 22647, df_num = 9
10	F = 183.0710, p = 0.0000, df_denom = 22644, df_num = 10	chi2 = 1832.4080, p = 0.0000, df = 10	chi2 = 1762.1002, p = 0.0000, df = 10	F = 183.0710, p = 0.0000, df_denom = 22644, df_num = 10
11	F = 177.9576, p = 0.0000, df_denom = 22641, df_num = 11	chi2 = 1959.5220, p = 0.0000, df = 11	chi2 = 1879.3987, p = 0.0000, df = 11	F = 177.9576, p = 0.0000, df_denom = 22641, df_num = 11
12	F = 165.1337, p = 0.0000, df_denom = 22638, df_num = 12	chi2 = 1983.7930, p = 0.0000, df = 12	chi2 = 1901.7238, p = 0.0000, df = 12	F = 165.1337, p = 0.0000, df_denom = 22638, df_num = 12
13	F = 226.8460, p = 0.0000, df_denom = 22635, df_num = 13	chi2 = 2952.5161, p = 0.0000, df = 13	chi2 = 2775.4087, p = 0.0000, df = 13	F = 226.8460, p = 0.0000, df_denom = 22635, df_num = 13
14	F = 227.6980, p = 0.0000, df_denom = 22632, df_num = 14	chi2 = 3191.8569, p = 0.0000, df = 14	chi2 = 2986.1697, p = 0.0000, df = 14	F = 227.6980, p = 0.0000, df_denom = 22632, df_num = 14
15	F = 208.2185, p = 0.0000, df_denom = 22629, df_num = 15	chi2 = 3127.5555, p = 0.0000, df = 15	chi2 = 2929.7290, p = 0.0000, df = 15	F = 208.2185, p = 0.0000, df_denom = 22629, df_num = 15

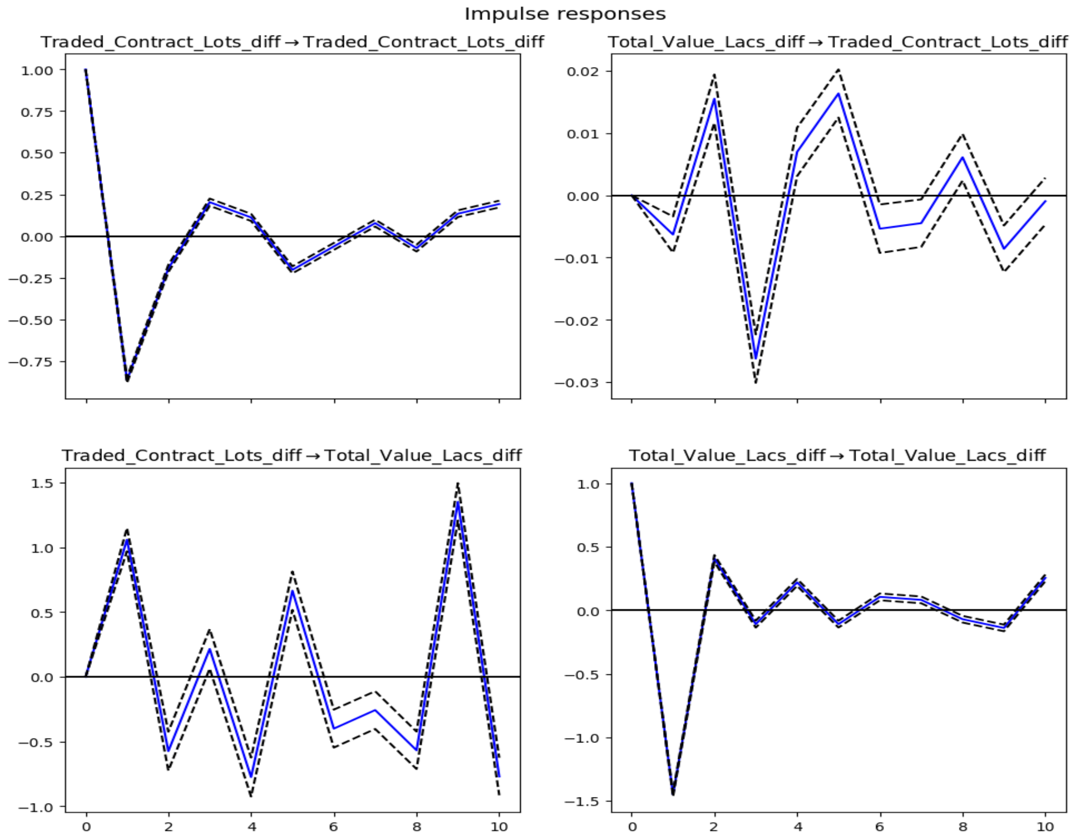
Hypothesis-Lead-lag relationship:

Null Hypothesis (H0): There is no lead-lag relationship between spot and futures prices of metals on MCX.

Alternative Hypothesis (H1): There is a significant lead-lag relationship between spot and futures prices of metals on MCX.

The Granger causality test results demonstrate consistently significant relationships, indicated by p-values of 0.0000, across various lag lengths ranging from 1 to 15. This statistical significance implies that past values of one variable (traded contract lots) can be used to predict future values of another variable (total value) within the futures market.The robust p-values suggest a strong lead-lag relationship between trading activity (measured by contract lots) and market value. In other words, fluctuations in the trading volume of futures contracts appear to precede and potentially influence changes in the overall market value, indicating a causal direction from trading activity to market price movements.While it is important to note that conclusions regarding spot prices cannot be directly drawn from these findings, the evidence strongly suggests that there exists a lead-lag relationship within the futures market itself. This relationship is likely relevant to the broader price discovery process, where futures market dynamics play a critical role in influencing asset pricing.

Figure - 1
Impulse Response Analysis: Traded Contract Lots and Total Value



The impulse response analysis aims to assess the dynamic interactions between "Traded Contract Lots" and "Total Value." The findings reveal several significant patterns:

1. Impact of Traded Contract Lots on Itself: A shock to the traded contract lots has a considerable and enduring effect on itself, with responses that decay over time. This finding implies that fluctuations in trading activity tend to influence future contract trading volumes persistently.
2. Impact of Total Value on Traded Contract Lots: A shock to the total value has a minor and brief impact on traded contract lots. This limited effect suggests that changes in total value do not substantially drive trading activities, indicating that other factors may be more influential.
3. Impact of Traded Contract Lots on Total Value: A shock to traded contract lots produces a significant and lasting effect on total value, with responses that gradually decline over time. This relationship indicates that trading activities significantly influence total trade values, marking trading activity as a critical determinant in the price discovery process.
4. Impact of Total Value on Itself: A shock to total value similarly exhibits a considerable and persistent effect on itself, demonstrating that changes in total value are self-reinforcing. Future movements in total value are thus influenced by its previous levels.

CONCLUSION

The Granger Causality Test results indicate a significant lead-lag relationship between trading activities (measured by traded contract lots) and market value (total value) in the futures market for metals on the Multi Commodity Exchange (MCX). The Augmented Dickey-Fuller (ADF) test confirmed that both series are stationary, reinforcing the reliability of subsequent analyses. Across multiple lag lengths (1 to 15), the Granger causality tests consistently produced statistically significant p-values (0.0000), rejecting the null hypothesis of no causal relationship. This robust statistical evidence suggests that fluctuations in the trading volume of futures contracts have predictive power over future changes in market value, highlighting the dynamic interplay between these two variables. Furthermore, while the findings do not directly address spot prices, they underscore the critical role of trading activities in the broader price discovery process within the futures market.

Managerial Implications

The implications of these findings for market participants, including traders and institutional investors, are profound. Understanding the lead-lag relationship can assist traders in making informed decisions regarding their trading strategies. For instance, the evidence that trading volumes can predict market value suggests that traders may benefit from monitoring contract lots to anticipate price movements. Additionally, market analysts and portfolio managers can leverage these insights to optimize their trading strategies and asset allocation decisions. By recognizing the causal influence of trading activity on market prices, firms can enhance their risk management practices and improve their responsiveness to market changes. Overall, the results provide a framework for informed trading decisions that can lead to better financial outcomes.

Societal Implications

From a societal perspective, the insights gained from the Granger causality test can enhance the overall transparency and efficiency of the futures market. By establishing a clear relationship between trading activities and market value, these findings can foster greater confidence among investors and promote increased participation in the commodities market. Moreover, heightened trading activity may contribute to better price discovery and resource allocation in the economy. Understanding these dynamics can also benefit policymakers, as it provides essential information for regulating futures markets effectively. Increased market participation can lead to more stable prices, ultimately benefiting consumers by providing better pricing mechanisms for essential commodities.

Future Scope

The future scope of this research is promising and can be expanded in several directions. Firstly, further investigations could explore the lead-lag relationships across different commodities within the MCX framework to understand whether similar dynamics hold across various asset classes. Additionally, researchers could incorporate other macroeconomic variables, such as interest rates or economic indicators, to assess their influence on trading activities and market values. Longitudinal studies that analyze changes over time may also yield valuable insights into how these relationships evolve under varying market conditions. Lastly, applying advanced machine learning techniques to predict market movements based on trading activities could provide practical applications for traders and investors, enhancing decision-making processes in the ever-changing landscape of financial markets.

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