Indian Commodity Derivatives Market : Structural Breaks and Price Discovery

U. Sarita Singha [1]
N. B. Singh [2]
Kelvin Mutum [3]

Abstract

Purpose : The purpose of this research was to determine structural breakpoints and examine the causal relationship between the spot and futures markets for 12 commodities that are traded in India.

Methodology : Data were obtained from the Multi Commodity Exchange of India Limited (MCX) website for both futures and spot price series of 12 commodities, including agricultural commodities (crude palm oil (CPO), mentha oil, and cotton), energy commodities (natural gas and crude oil), precious metals (silver and gold), and base metals (lead, zinc, aluminum, copper, and nickel). Structural breaks were identified using a multiple breakpoint test, and the price series were segmented into sub-periods. Subsequently, the Granger causality test was conducted within a vector autoregressive (VAR) framework to examine causal relationships between the spot and futures markets. This analysis was conducted for the entire study period and for sub-periods identified by structural breaks.

Findings : Bidirectional relationships were observed for the whole period across all commodities, indicating market efficiency. Nonetheless, in certain sub-periods, unidirectional causality was noted, indicating potential structural fractures brought on by events influencing market efficiency on the political or economic front.

Practical Implications : The findings of this study are valuable for various stakeholders, including individual and institutional investors, policymakers shaping regulatory frameworks, market regulators, exchange facilitators, and other relevant authorities. These insights contributed to informed decision-making, robust policy formulation, improved regulatory oversight, and the enhancement of market integrity and stability.

Originality : This study contributed to the literature by considering structural breakpoints in the analysis of price discovery and market efficiency in the Indian commodity derivatives market, an aspect that has been relatively underexplored in previous studies.

Keywords : market efficiency, agricultural commodities, causality test, derivatives, multiple breakpoints

JEL Classification Codes : C32, G13, G14, Q02, Q11

Paper Submission Date : September 25, 2023 ; **Paper sent back for Revision :** April 23, 2024 ; **Paper Acceptance Date :** June 10, 2024 ; **Paper Published Online :** August 14, 2024

[1] *Research Scholar,* Department of Humanities and Social Sciences, National Institute of Technology Silchar, NIT Road, Fakiratilla, Silchar - 788 010, Assam. (Email : nainachanu.123@gmail.com)
ORCID iD : https://orcid.org/0000-0002-6751-014X

[2] *Professor,* Department of Humanities and Social Sciences, National Institute of Technology Silchar, NIT Road, Fakiratilla, Silchar - 788 010, Assam. (Email : nbsingh@hum.nits.ac.in) ; ORCID iD : https://orcid.org/0000-0001-8769-7645

[3] *Assistant Professor (Corresponding Author),* Department of Humanities and Social Sciences, National Institute of Technology Meghalaya, Bijni Complex, Laitumkhrah, Shillong - 793 003, Meghalaya. (Email : kelvinmutum@gmail.com)
ORCID iD : https://orcid.org/0000-0002-4844-380X

DOI : https://doi.org/10.17010/ijf/2024/v18i8/174240

Structural breaks or shocks in time-series data are caused by political or economic events that deviate from the norm. By locating these breakpoints, estimations can be made more accurate, and their future effects can be controlled. When data spans a long time, multiple breakpoints may arise. It is possible to accommodate both known and unknown breakpoints in the test models that researchers have built for the analysis of structural breaks. Initially, studies of structural changes used known break dates, referencing financial or economic events from news reports. The first test model, introduced by Chow (1960), used a known single break date. Quandt (1960) later adapted this model for unknown break dates. Significant contributions by Andrews (1993) led to the Quandt-Andrews framework. This approach was extended by Bai (1997) and Bai and Perron (1998, 2003) to take into consideration several uncertain break dates.

This paper identifies multiple unknown breakpoints in the price series data of commodity derivatives in both the spot and futures markets using the Bai–Perron test model. The causal connection between these marketplaces is also investigated. This approach is innovative in evaluating market efficiency in reaction to structural changes since it addresses price discovery in Indian commodity derivatives while considering structural breaks, a topic that has not been extensively studied. To examine the causal relationship between the spot and futures markets within each sub-period, the data were first translated into return series, which made them stationary. Information should ideally flow instantly between both markets in an efficient market; hence, lead–lag connections should not exist. However, due to higher liquidity and lower costs, information flows faster in the futures market than in the spot market, causing price changes to reflect market information more quickly in the futures market. Critics argue that excessive speculation in the futures market can lead to disproportionate changes, raising concerns about market efficiency and utility.

There are a lot of studies that highlight market efficiency in the literature on the price discovery mechanism in the Indian commodity derivative market. To determine market efficiency, these studies often examine the short- and long-term causal linkages as well as the long-term co-integration between the spot and futures markets. However, fewer studies have considered structural breaks in analyzing market efficiency through the price discovery mechanism, necessitating a more in-depth analysis.

This study aims to fill this gap by identifying structural breakpoints and examining the causal relationship between the futures and spot markets of Indian commodity derivatives traded on the Multi Commodity Exchange of India Ltd. (MCX). The commodities analyzed include aluminum, zinc, lead, gold, silver, natural gas, crude oil, crude palm oil (CPO), mentha oil, cotton, nickel, and copper, covering the period from 2006 to 2021. The Bai–Perron test and the vector autoregressive (VAR) Granger causality test were employed to determine the causal relationship between the spot and futures markets, considering structural breaks.

Literature Review

Indian commodity derivative market, after a long halt, restarted in early 2003 and underwent massive growth (Sonia, 2023). There has been a ban on trading certain commodities on and off in an attempt to stabilize the market from excessive speculations on which critics did discussions with statistical evidence. The literature available in its initial phase was mainly concerned with the market efficiency of agricultural commodities (Rani & Kumar, 2023). Numerous studies were conducted on the price discovery of the Indian commodity derivative market, which was one of the main objectives behind introducing the derivative market. Various approaches were adopted to analyze the price discovery mechanism. The most commonly used method is to examine the cointegration between the spot market and the futures market in the long run and their short-run causal relationship (Ali & Gupta, 2011; Gupta et al., 2018; Irfan & Hooda, 2017; Kaura et al., 2019; Lethesh & Reddy, 2023; Purohit et al., 2015; Seth & Sidhu, 2021).

Ali and Gupta (2011) analyzed guar seed, wheat, maize, rice, soybean, chickpea, red lentil, castor seed, black lentil, cashew, pepper, and sugar grade M and found that most of the commodities were cointegrated in the long run; futures could predict spot market; and there also existed bidirectional causality. The study conducted by Kumar and Pandey (2013) for gold, soybean, guar seed, silver, maize, castor seed, copper, aluminum, zinc, natural gas, and crude oil revealed the existence of some inefficiency in the short run of all the commodities but long-run equilibrium in most of the commodities. Sehgal et al. (2013) observed a cointegration relationship between futures and spot in MCX metal, MCX Comdex, MCX Energy, guar seed, lead, soybean, chana, crude oil, natural gas, zinc, and copper. All the commodities were found to have bidirectional relationships in the short run except MCX Comdex, MCX metal, guar seed, soybean, and natural gas. Inoue and Hamori (2014) analyzed the commodity index and concluded the presence of cointegration and that the market efficiency has increased in recent years. Purohit et al. (2015) studied the nature of non-precious metals such as aluminum, zinc, copper, nickel, and lead. A long-term cointegration and bidirectional causal relationship were observed in all the metals examined.

Irfan and Hooda (2017) studied pepper, chili, barley, sugar, chana (Bengal gram whole), turmeric, wheat, soybean, mustard-seed, and maize and found that there existed long-run equilibrium and a unidirectional causal relationship in the short run. Inani's (2018) research indicated that the spot market led for mustard seed, guar seed, chana (chickpea), jeera, and cottonseed, while the futures markets led for turmeric, cottonseed, castor oil, sugar, coriander, and soy oil. Perumandla and Kurisetti (2018) found a unidirectional causality from the MCX Comdex index to the Dhaanya index. Gupta et al. (2018) examined natural gas, castor seed, silver, guar seed, crude oil, copper, gold, and nickel. They found the futures market to be cointegrated with the spot market. Although information efficiency existed, the market was skewed and inefficient. Joarder and Mukherjee (2021) analyzed the lead–lag relationship of cottonseed oilcake, soybean, mustard seed, castor seed, soymeal, and refined soy oil and found that still, the futures market did not act as a price discovery tool and the past values of spot market played as a decision-making reference point. Kaura et al. (2019) found cardamom, cotton, CPO, and mentha oil to exhibit a long-run equilibrium, but in the short run, there existed an opportunity for exploitable arbitrage.

Manogna and Mishra (2020) suggested the futures markets leading for chana, coriander, guar seed, turmeric, soybean seed, and castor seed, and the spot market leading in the case of jeera, rape mustard seed, and cotton seed. Seth and Sidhu (2021) found that futures led the spot market in the long run for crude oil and natural gas ; whereas, spot led the futures market in the case of post-crisis period. Kaura and Rajput's (2021) study revealed that the spot market helped discover prices for agricultural commodities, and the futures market helped discover prices for non-agricultural commodities. Lethesh and Reddy (2023) analyzed the price discovery efficiency of agricultural commodities in India and found chana, jeera, maize, moong, and soybean were efficient, but coriander and cotton cake were led by the spot market, and barley, turmeric, and wheat were led by the futures market.

There have been several studies of structural breaks in financial data (Parthasarathy, 2019), but few studies were done considering the structural breaks while analyzing the price discovery of the commodity derivative market. Peri et al. (2013) analyzed structural breaks in spot and futures markets of commodity derivatives using the sequential test method of the Bai–Perron test and then Granger causality. Zarei et al. (2015) also studied structural breaks in the exchange rate series using the global information criteria method of the Bai–Perron test.

Thus, multiple structural breaks need to be examined in a long period of financial data and their impact on the market efficiency with the assumption that there would be breaks because of certain economic or political events. Therefore, further analysis of the price discovery mechanism of the commodity market in India is highly pertinent.

Data and Methodology

The approach adopted in this study was exploratory research. Daily statistics on futures and spot markets were gathered from the website of MCX, the national commodity exchange in India with the highest turnover. Here, we have taken commodities of economic importance according to the Multi Commodity Exchange of India Limited (2022). Samples consist of 12 commodities, i.e., three agricultural commodities (cotton, CPO, and mentha oil), two energy commodities (crude oil and natural gas), five base metals (zinc, lead, aluminum, nickel, and copper) and two precious metals (silver and gold). The Indian commodity market gained momentum in 2006. Thus, from 2006 to 2021, data for this study were gathered.

Nevertheless, a small number of commodities experienced erratic or nonexistent trading at the start of the sample period, which was disregarded in the research. Price series were made using contracts that have their expiration date the nearest. Missing data were eliminated and prices were matched in both markets to create the spot and futures price series. Table 1 provides information on the study period and the quantity of data for each commodity.

Table 1 shows that the majority of the commodities under investigation have multiple observations totaling over 4,000, with the exception of cotton and CPO, whose trading durations were shorter than those of the other commodities.

The *p*-value for each series is significant, rejecting the null hypothesis that the data are normally distributed and accepting the alternative hypothesis that the data are not. The Jarque–Bera test was used to determine whether the price series was normal. The return series was constructed by taking the logarithmic return of the price series by using Equation (1).

$$r_t = \ln\left(\frac{p_t}{p_{t-1}}\right) * 100 \qquad (1)$$

where, r_t = return at time t, p_{t-1} = price at time t–1, and p_t = price at time t.

The stationarity test was conducted using the Augmented Dickey-Fuller (ADF) test on the price series and return series and then applied the Bai–Perron model for multiple breakpoint tests to find out structural breaks in the series. VAR Granger causality test was applied on the return series for the whole period and the sub-periods

Table 1. *Sample Details*

Commodity	Trading Period	Number of Observation
Aluminum	January 4, 2006 to December 31, 2021	4447
Copper	January 3, 2006 to December 31, 2021	4434
Cotton	October 4, 2011 to December 31, 2021	2657
CPO	June 10, 2008 to December 31, 2021	3642
Crude Oil	January 2, 2006 to December 31, 2021	4465
Gold	January 2, 2006 to December 31, 2021	4436
Lead	July 2, 2007 to December 31, 2021	4010
Mentha Oil	November 3, 2006 to December 31, 2021	4121
Natural Gas	October 19, 2006 to December 31, 2021	4208
Nickel	November 1, 2006 to December 31, 2021	4211
Silver	January 2, 2006 to December 31, 2021	4337
Zinc	March 30, 2006 to December 31, 2021	4394

Note. * Trading days were Monday through Saturday until March 2014. As of April 2014, Monday through Friday are the trading days.

when there were breaks in the return series to study the causal relationships. Lag values were chosen using the Akaike information criterion (AIC). The above analysis was carried out in EViews software.

Stationarity Test

Stationarity refers to the state of statistical parameters, like mean, variance, etc., that stay constant over time. The ADF test was applied to study the stationarity of the data. It was conducted by considering the lagged values of the variable. It is denoted in Equation (2).

$$\Delta p_t = \beta_1 + \beta_2 t + \delta p_{t-1} + \sum\nolimits_{i=1}^{n} \alpha_i \Delta p_{t-i} + \varepsilon_t \tag{2}$$

where, ε_t is a pure white noise error term, p_t is the variable at time t, $\beta_1 + \beta_2 t$ is drift around a stochastic trend term, $\Delta p_t = p_t - p_{t-1}$ and $\delta = \rho - 1$, where $-1 \leq \rho \leq 1$.

The null hypothesis (H_{01}) is that $\delta = 0$, i.e., the time series is non-stationary, and the alternate hypothesis (H_{a1}) is that $\delta \neq 0$, i.e., the time series is stationary.

Multiple Breakpoint Test

Bai and Perron (2003) proposed a multiple linear regression with n breaks, as given in Equation (3).

$$b_t = a_t^{'} \beta + c_t^{'} \delta_n + e_t, \; t = T_{n-1} + 1, \ldots, T_n \tag{3}$$

where, a_t and c_t are vectors of covariates, b_t is the observed dependent variable at time t, β and δ_n are the corresponding vectors of coefficients, e_t is the disturbance at time t, and n is the number of breaks in the $n + 1$ regimes. The breakpoints ($T_1 \ldots . T_n$) are treated as unknown. It aims to estimate the unknown regression coefficients together with the breakpoints when a number of observations on the dependent and the vectors of covariates (a_t, b_t, c_t) are available. The null hypothesis (H_{02}) is that there is no significant change or disturbance denoting instability, implying no breaks versus an alternate hypothesis (H_{a2}) of an arbitrary number of breaks.

This paper employs the global information criteria approach for estimating multiple breakpoints, which offers distinct advantages such as not requiring the computation of the coefficient of covariance (Zarei et al., 2015). Breakpoints were estimated using minimizers of the sum of squared residuals. Pre-whitened residuals were used in quadratic spectral kernel-based covariance estimation to adjust for serial correlation in the errors. The bandwidth of the kernel was determined using the Andrews AR (1) method. Selection criteria for the optimal number of breaks were based on a modified Schwarz criterion (LWZ).

Vector Autoregression (VAR) Granger Causality Test

VAR Granger causality test was performed to examine the causal relationship between the spot and futures market using returns price series. The causation relationship was examined using the block exogeneity test in the VAR environment. VAR equation of two variables s and f of order n is given by Equations (4) and (5), respectively.

$$s_t = \beta_{so} + \beta_{ss1} s_{t-1} + \ldots + \beta_{ssn} s_{t-n} + \beta_{sf1} f_{t-1} + \ldots + \beta_{sfn} f_{t-n} + v_t^s \tag{4}$$

$$f_t = \beta_{fo} + \beta_{fs1} s_{t-1} + \ldots + \beta_{fsn} s_{t-n} + \beta_{ff1} f_{t-1} + \ldots + \beta_{ffn} f_{t-n} + v_t^f \tag{5}$$

where, s_t = spot price at time t, f_t = futures price at time t, β_{sfn} = coefficient of futures price for spot price at lag n, β_{fsn} = coefficient of spot price for futures price at lag n, and v_t = innovation term, and β_o is a constant.

The null hypothesis (H_{03}) is that the independent variable does not cause the dependent variable, and the alternate hypothesis (H_{a3}) is that the independent variable causes the dependent variable.

Analysis and Results

Daily price series descriptive statistics for the futures and spot of the 12 commodities under study, which comprise mean, maximum, minimum, median, skewness, kurtosis, and standard deviation are summarized in Table 2.

Table 2 reveals that the difference in the mean values and the difference in median values of the spot and futures markets were small. The extended time span we used for the study meant that all of the price time series had a significant gap between their maximum and lowest values; as a result, their standard deviations were also bigger. All the price series were positively skewed except lead futures and lead spot price series. Aluminum, copper, cotton, CPO, mentha oil, natural gas, and nickel have kurtosis values above 3, i.e., they were leptokurtic. Crude

Table 2. ***Descriptive Statistics of Daily Price Series***

Price Series	Parameters						
	Mean	Median	Maximum	Minimum	Standard Deviation	Skewness	Kurtosis
Aluminum Futures	119.5198	113.0500	255.3500	62.6000	26.9154	1.5719	7.1193
Aluminum Spot	119.5415	112.4500	268.9500	62.5500	28.3169	1.6749	7.4102
Copper Futures	393.1791	399.8000	797.5000	141.3500	108.7029	1.1312	5.7553
Copper Spot	391.7789	394.2000	825.6500	135.6500	110.0585	1.1895	5.9260
Cotton Futures	19365.3500	19,180	33,790	13,990	3117.3820	1.5484	7.1717
Cotton Spot	19393.5100	19,140	33,760	14,420	3151.2490	1.4072	6.4234
CPO Futures	545.2913	518.9000	1258.3000	232.3000	191.0594	1.7282	6.2337
CPO Spot	546.6005	519.3000	1,281	240	194.7096	1.7713	6.3922
Crude Oil Futures	3978.7090	3,738	7,507	1	1113.3640	0.4377	2.5513
Crude Oil Spot	3969.4700	3,733	7,527	887	1115.4830	0.4344	2.5342
Gold Futures	25575.5700	27,561	55,845	7,658	11357.9200	0.3362	2.6179
Gold Spot	25511.9200	27,566	55,922	7,640	11278.6100	0.3204	2.6258
Lead Futures	124.1825	122.8500	192.6500	42.0500	27.9568	–0.1442	2.9870
Lead Spot	124.1407	122.6500	195.5000	41.5000	28.4146	–0.1387	2.9437
Mentha Oil Futures	966.3248	935.5000	2570.3000	416.2000	359.2144	0.7600	3.7949
Mentha Oil Spot	1066.6220	1053.300	2769.3000	477.1000	400.0887	0.6214	3.4532
Natural Gas Futures	221.0350	198.3000	587.3000	100.2000	74.3255	1.6267	6.5709
Natural Gas Spot	220.4044	197.7000	587.9000	99	74.3136	1.6242	6.5697
Nickel Futures	973.2439	932.8000	2,240	455	287.7056	1.3155	6.0633
Nickel Spot	971.6943	924.1000	2259.9000	439.9000	293.5463	1.3607	6.1931
Silver Futures	39088.9400	39,118	76,052	13,087	14969.5100	0.1920	2.1580
Silver Spot	38736.7200	38,634	73,755	13,200	14809.1500	0.1983	2.1680
Zinc Futures	139.4008	125.8500	308.4000	51	48.8592	0.6397	2.7435
Zinc Spot	139.3363	125.2000	320.5000	49.4500	49.7966	0.6578	2.7717

oil, gold, and lead have kurtosis values lesser than 3 i.e., they were platykurtic. Aluminum, copper, cotton, CPO, natural gas, and nickel have highly positive skewness and high kurtosis values much higher than the other commodities, implying favorable investment options with high positive returns. The stationarity test applying ADF test results are shown in Table 3.

Table 3 shows that the *p*-values for the futures and spot price series of all commodities were insignificant. Therefore, we accept the null hypothesis (H_{01}), indicating that the price series in both the futures and spot markets were non-stationary. Conversely, the futures and spot return time series were stationary, as the *t*-statistics were significantly greater than the critical values, leading us to reject the unit root null hypothesis (H_{01}) and accept the alternate hypothesis (H_{a1}).

A regression model was used, using a constant regressor and the return price series of each commodity in the futures and spot markets as the dependent variable. The serial correlation that varies between regimes was taken into consideration using the HAC covariance estimation. The model allows for a maximum of five breaks, with a trimming percentage of 15%, ensuring at least 15 observations in each regime. The LWZ criteria

Table 3. *Stationarity Test*

Variables	Price Series		Return Series	
	t-statistics	*p*-value	*t*-statistics	*p*-value
Aluminum Futures	0.6504	0.9911	–68.1841	0.0001
Aluminum Spot	0.1420	0.9688	–71.3761	0.0001
Copper Futures	–0.4543	0.8974	–18.0327	0.0000
Copper Spot	–0.6953	0.8461	–12.1521	0.0000
Cotton Futures	0.9659	0.9963	–56.4101	0.0001
Cotton Spot	0.4145	0.9836	–13.2950	0.0000
CPO Futures	–0.0750	0.9503	–11.6819	0.0000
CPO Spot	–0.3854	0.9093	–16.5731	0.0000
Crude Oil Futures	–2.5265	0.1092	–32.3783	0.0000
Crude Oil Spot	–2.2796	0.1787	–11.3221	0.0000
Gold Futures	–0.1417	0.9431	–16.6331	0.0000
Gold Spot	–0.2156	0.9341	–19.6174	0.0000
Lead Futures	–1.7164	0.4228	–19.7616	0.0000
Lead Spot	–1.6789	0.4420	–64.7015	0.0001
Mentha Oil Futures	–2.6353	0.0859	–46.6971	0.0001
Mentha Oil Spot	–2.3576	0.1541	–12.5408	0.0000
Natural Gas Futures	–3.1197	0.0252	–34.0836	0.0000
Natural Gas Spot	–3.2635	0.0167	–34.0043	0.0000
Nickel Futures	–1.8011	0.3804	–22.1027	0.0000
Nickel Spot	–2.0566	0.2627	–24.0144	0.0000
Silver Futures	–1.5234	0.5218	–19.6576	0.0000
Silver Spot	–1.6774	0.4428	–19.4118	0.0000
Zinc Futures	0.2441	0.9753	–68.0304	0.0001
Zinc Spot	–0.1697	0.9398	–67.8103	0.0001

Note.* Critical values at 1%, 5%, and 10% levels were –3.4319, –2.8621, and –2.5671, respectively.

Table 4. ***Multiple Breakpoint Test***

Variables	Break Date(s) Identified	LWZ Criterion Value
Aluminum Futures	Four: 11/10/2008, 17/12/2010, 27/09/2016, 10/05/2019	5.5021
Aluminum Spot	Four: 10/10/2008, 16/12/2010, 27/09/2016, 10/05/2019	5.5516
Copper Futures	Five: 7/07/2008, 5/10/2010, 27/02/2014, 4/10/2016, 15/05/2019	8.4037
Copper Spot	Five: 8/07/2008, 6/10/2010, 27/02/2014, 4/10/2016, 15/05/2019	8.4534
Cotton Futures	Four: 5/03/2013, 1/09/2014, 2/06/2016, 11/06/2020	15.5181
Cotton Spot	Four: 14/03/2013, 24/09/2014, 6/06/2016, 11/06/2020	15.5375
CPO Futures	Four: 25/10/2010, 21/09/2012, 17/03/2016, 7/11/2019	9.0652
CPO Spot	Four: 22/10/2010, 21/09/2012, 22/03/2016, 7/11/2019	9.1110
Crude Oil Futures	Four: 18/03/2008, 7/11/2011, 27/11/2014, 6/11/2017	13.2240
Crude Oil Spot	Four: 18/03/2008, 8/11/2011, 1/12/2014, 7/11/2017	13.2393
Gold Futures	Five: 29/01/2009, 30/07/2011, 10/10/2013, 14/06/2016, 4/06/2019	15.8177
Gold Spot	Five: 30/01/2009, 3/08/2011, 23/10/2013, 24/06/2016, 4/06/2019	15.8456
Lead Futures	Four: 23/09/2010, 8/09/2012, 25/10/2016, 9/07/2019	5.4459
Lead Spot	Four: 24/09/2010, 10/09/2012, 30/09/2016, 13/08/2019	5.4408
Mentha Oil Futures	Four: 8/10/2010, 1/04/2013, 18/01/2017, 18/07/2019	10.5146
Mentha Oil Spot	Four: 7/10/2010, 1/04/2013, 18/01/2017, 18/07/2019	10.6285
Natural Gas Futures	Four: 13/01/2009, 10/10/2012, 19/01/2015, 22/05/2018	7.8790
Natural Gas Spot	Four: 14/01/2009, 12/10/2012, 21/01/2015, 23/05/2018	7.8836
Nickel Futures	Four: 5/12/2008, 30/12/2010, 25/03/2015, 1/07/2019	10.8239
Nickel Spot	Four: 5/12/2008, 30/12/2010, 25/03/2015, 1/07/2019	10.8721
Silver Futures	Four: 13/03/2008, 8/11/2010, 15/04/2013, 3/06/2019	17.3847
Silver Spot	Four: 13/03/2008, 10/11/2010, 15/04/2013, 3/06/2019	17.4173
Zinc Futures	Five: 2/06/2008, 2/08/2010, 12/08/2013, 20/10/2016, 21/05/2019	6.2447
Zinc Spot	Five: 2/06/2008, 3/08/2010, 9/08/2013, 5/09/2016, 29/03/2019	6.2641

Note. * Breaks are given in DD/MM/YYYY.

(Zarei et al., 2015) were used to determine the optimal number of breakpoints, with the identified break date marking the first day of the subsequent regime. Table 4 presents the test results for the multiple breakpoints.

Table 4 reveals that there were four break dates in all the commodities price series, except copper, gold, and zinc, having five break dates. The first sub-period exists between the price series data starting date to the last trading day before the first break date. This sub-period is also called a regime. The second regime or sub-period starts from the first break date to the last trading day before the second break date and so on till the last trading day of the data, i.e., December 31, 2021. Therefore, we got five sub-periods or regimes in all the commodities price series, except copper, gold, and zinc having six sub-periods.

The return series are formed by applying Equation (1) to the price series. The return series were stationary in nature, and therefore, the VAR Granger causality analysis was conducted first for the whole period and then for all the regimes or sub-periods. The lag values are selected using the AIC criteria. Table 5 represents the test results of VAR Granger causality for the whole period under study.

Table 5 shows that for all commodities, whether the futures return series is the dependent variable and the spot return series is the independent variable, or vice versa, the null hypothesis (H_{03}) is rejected, and the alternate

Table 5. ***VAR Granger Causality Test for the Whole Period***

Commodity	Dependent Variable	Independent Variable	χ^2	*p*-value
Aluminum	Futures	Spot	81.14335	0.0000
	Spot	Futures	1627.672	0.0000
Copper	Futures	Spot	38.31806	0.0001
	Spot	Futures	10254.07	0.0000
Cotton	Futures	Spot	23.03207	0.0061
	Spot	Futures	254.0513	0.0000
CPO	Futures	Spot	207.5406	0.0000
	Spot	Futures	393.7981	0.0000
Crude Oil	Futures	Spot	251.8279	0.0000
	Spot	Futures	9587.568	0.0000
Gold	Futures	Spot	49.69583	0.0000
	Spot	Futures	2363.532	0.0000
Lead	Futures	Spot	50.36452	0.0350
	Spot	Futures	2028.018	0.0000
Mentha Oil	Futures	Spot	480.7377	0.0000
	Spot	Futures	98.30703	0.0000
Natural Gas	Futures	Spot	46.45103	0.0368
	Spot	Futures	13912.01	0.0000
Nickel	Futures	Spot	61.96462	0.0000
	Spot	Futures	2198.440	0.0000
Silver	Futures	Spot	34.39389	0.0329
	Spot	Futures	2306.004	0.0000
Zinc	Futures	Spot	107.2441	0.0000
	Spot	Futures	1971.063	0.0000

Note. * Significant at the 5% level.

hypothesis (H_{a3}) is accepted, indicating bidirectional causality at a 5% significance level. This implies that variations in the futures market cause corresponding variations in the spot market and vice versa. Consequently, it can be concluded that the Indian commodity derivative market is efficient, with information flowing spontaneously between the futures and spot markets.

Causality test was applied in a VAR environment for each of the sub-periods or regimes after considering the multiple breaking points. The test results are shown in Table 6.

Table 6 reveals that, at the 5% significant level, there is both unidirectional and bidirectional causality. It is discovered that the futures market Granger causes the spot market in circumstances of unidirectional causality for all commodities, demonstrating an efficient mechanism for price discovery—the futures market's main goal. However, in the case of mentha oil, the spot market Granger causes the futures market. The market is generally efficient, with the futures market often leading the spot market during periods of structural change, except for mentha oil, where this was not the case. Thus, it may be concluded that short-term changes in futures or spot markets due to political or economic events may have an impact on market efficiency. Although the market seems

Table 6. *VAR Granger Causality Test for the Sub-Periods*

Commodity	RME 1	RME 2	RME 3	RME 4	RME 5	RME 6
Aluminum	FUT ↔ SPT	FUT → SPT	FUT → SPT	FUT ↔ SPT	FUT → SPT	
Copper	FUT → SPT	FUT ↔ SPT	FUT ↔ SPT	FUT → SPT	FUT → SPT	FUT ↔ SPT
Cotton	FUT → SPT	FUT ↔ SPT	FUT → SPT	FUT → SPT	FUT ↔ SPT	
CPO	FUT ↔ SPT	FUT ↔ SPT	FUT ↔ SPT	FUT ↔ SPT	FUT ↔ SPT	
Crude Oil	FUT → SPT	FUT ↔ SPT	FUT → SPT	FUT ↔ SPT	FUT ↔ SPT	
Gold	FUT ↔ SPT	FUT → SPT	FUT ↔ SPT	FUT ↔ SPT	FUT → SPT	FUT ↔ SPT
Lead	FUT → SPT	FUT → SPT	FUT ↔ SPT	FUT → SPT	FUT ↔ SPT	
Mentha Oil	FUT ↔ SPT	FUT ↔ SPT	FUT ↔ SPT	FUT ↔ SPT	FUT ← SPT	
Natural Gas	FUT → SPT	FUT → SPT	FUT ↔ SPT	FUT ↔ SPT	FUT → SPT	
Nickel	FUT → SPT	FUT ↔ SPT	FUT → SPT	FUT → SPT	FUT ↔ SPT	
Silver	FUT ↔ SPT	FUT → SPT	FUT ↔ SPT	FUT ↔ SPT	FUT ↔ SPT	
Zinc	FUT ↔ SPT	FUT → SPT	FUT ↔ SPT	FUT → SPT	FUT ↔ SPT	FUT → SPT

Note. * (1) RME stands for Regime, FUT stands for Futures, SPT Stands for Spot, ↔ Stands for Bidirectional, and → Stands for Unidirectional.

(2) Significant at the 5% level.

efficient over the long term, changes in market efficiency are revealed when it is examined on a sub-period basis while taking structural breaks into account. This method offers a clearer understanding of how disruptions brought about by political or economic events affect the effectiveness of the market.

Conclusions and Policy Implications

The price discovery mechanism of the Indian commodity derivative market was examined for cotton, CPO, mentha oil, crude oil, aluminum, natural gas, zinc, lead, copper, silver, gold, and nickel using data from the MCX. The price series data are non-stationary, while the return series data are stationary. The Bai–Perron test for multiple breakpoints was applied to the price series, identifying unknown break dates using the LWZ criteria. The return time series for the full study period was then subjected to the VAR Granger causality test, which demonstrated bidirectional causality between the futures and spot markets for every commodity under investigation. This shows that the market is efficient and capable of forecasting one another.

These results are consistent with earlier research on lead, zinc, crude oil, and zinc by Ali and Gupta (2011); zinc, lead, copper, and crude oil by Sehgal et al. (2013); and lead, zinc, nickel, aluminum, and copper by Purohit et al. (2015). In sub-periods, both bidirectional and unidirectional causality are observed between the spot and futures markets for all commodities. The futures market generally led the spot market when unidirectional causality was present, with the exception of mentha oil, in which case the spot market led the futures market. Although the market appears efficient over a long period, structural changes due to economic or political events affect efficiency, as evidenced by the structural breaks. This finding underscores the importance of considering structural breaks for a more comprehensive understanding of market efficiency.

The research outcomes hold significance for players in the commodity market, including exchanges, investors, policymakers, regulators, and other relevant parties operating on a national and global scale. The study is important for professionals, researchers, and regulators because of the commodities market's crucial responsibilities in risk management and asset allocation, both of which are vital for economic growth.

Limitations of the Study and Scope for Further Research

The research was restricted to the spot and futures daily closing prices of the commodities, so intra-day data and spectral analysis could be used to assess the degree of disruption in the data. Since the analysis was conducted using MCX data, a similar study might be conducted using data from other commodities derivative exchanges to strengthen the study's conclusions.

Authors' Contribution

The research endeavor was enriched by the collaborative efforts of U. Sarita Singha, Dr. N. B. Singh, and Dr. Kelvin Mutum, each contributing significantly to different phases. Initially, U. Sarita Singha took the lead, conceptualizing the research framework, and conducting a thorough literature review. Dr. N. B. Singh and Dr. Kelvin Mutum provided valuable inputs by scrutinizing the methodology and supervising the study's progression. U. Sarita Singha took charge of data collection from the MCX website and subsequently conducted the analysis using EViews software. All authors actively participated in the interpretation of the data, holding talks and deliberations to guarantee a thorough comprehension of the findings in connection to the study objectives. This collaborative approach enhanced the depth and accuracy of the interpretation process, reflecting the collective expertise and contributions of all authors. U. Sarita Singha worked closely with Drs. N. B. Singh and Kelvin Mutum during the manuscript's preparation, incorporating their suggestions and insights into the writing process. They worked together to ensure that the manuscript was precise and cohesive, demonstrating the collective expertise and hard work of all the authors.

Conflict of Interest

The authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

Funding Acknowledgment

The authors received no financial support for the research, authorship, and/or for the publication of this article.

References

Ali, J., & Gupta, K. B. (2011). Efficiency in agricultural commodity futures markets in India: Evidence from cointegration and causality tests. *Agricultural Finance Review*, *71*(2), 162–178. https://doi.org/10.1108/00021461111152555

Andrews, D. W. (1993). Tests for parameter instability and structural change with unknown change point. *Econometrica*, *61*(4), 821–856. https://doi.org/10.2307/2951764

Bai, J. (1997). Estimating multiple breaks one at a time. *Econometric Theory*, *13*(3), 315–352. https://doi.org/10.1017/s0266466600005831

Bai, J., & Perron, P. (1998). Estimating and testing linear models with multiple structural changes. *Econometrica*, *66*(1), 47–78. https://doi.org/10.2307/2998540

Bai, J., & Perron, P. (2003). Computation and analysis of multiple structural change models. *Journal of Applied Econometrics*, *18*(1), 1–22. https://doi.org/10.1002/jae.659

Chow, G. C. (1960). Tests of equality between sets of coefficients in two linear regressions. *Econometrica*, *28*(3), 591–605. https://doi.org/10.2307/1910133

Gupta, S., Choudhary, H., & Agarwal, D. R. (2018). An empirical analysis of market efficiency and price discovery in the Indian commodity market. *Global Business Review*, *19*(3), 771–789. https://doi.org/10.1177/0972150917713882

Inani, S. K. (2018). Price discovery and efficiency of Indian agricultural commodity futures market: An empirical investigation. *Journal of Quantitative Economics*, *16*(1), 129–154. https://doi.org/10.1007/s40953-017-0074-7

Inoue, T., & Hamori, S. (2014). Market efficiency of commodity futures in India. *Applied Economics Letters*, *21*(8), 522–527. https://doi.org/10.1080/13504851.2013.872751

Irfan, M., & Hooda, J. (2017). An empirical study of price discovery in commodities futures market. *Indian Journal of Finance, 11*(3), 41–57. https://doi.org/10.17010/ijf/2017/v11i3/111648

Joarder, S., & Mukherjee, D. (2021). The lead–lag relationship between futures and spot price—A case of the oil and oilseed contracts traded on Indian exchange. *Arthaniti: Journal of Economic Theory and Practice*, *20*(1), 7–33. https://doi.org/10.1177/0976747919842689

Kaura, R., & Rajput, N. (2021). Future–spot relationship in commodity market: A comparison across commodity segments in India. *Global Business Review*. https://doi.org/10.1177/09721509211017291

Kaura, R., Kishor, N., & Rajput, N. (2019). Arbitrage, error correction, and causality: Case of highly traded agricultural commodities in India. *Indian Journal of Finance*, *13*(9), 7–21. https://doi.org/10.17010/ijf/2019/v13i9/147095

Kumar, B., & Pandey, A. (2013). Market efficiency in Indian commodity futures markets. *Journal of Indian Business Research*, *5*(2), 101–121. https://doi.org/10.1108/17554191311320773

Lethesh, M., & Reddy, C. V. (2023). Price discovery mechanism in the Indian agricultural commodity futures market – An empirical analysis. *Indian Journal of Finance*, *17*(12), 8–25. https://doi.org/10.17010/ijf/2023/v17i12/172823

Manogna, R. L., & Mishra, A. K. (2020). Price discovery and volatility spillover: An empirical evidence from spot and futures agricultural commodity markets in India. *Journal of Agribusiness in Developing and Emerging Economies*, *10*(4), 447–473. https://doi.org/10.1108/jadee-10-2019-0175

Multi Commodity Exchange of India Limited. (2022). *Commodity insights year book - 2022*. https://www.mcxindia.com/docs/default-source/about-us/commodity-insights-yearbook/2022/commodity-insights-yearbook-2022---statistics.pdf?sfvrsn=4c33ba90_2

Parthasarathy, S. (2019). Revisiting the weak form efficiency with structural breaks: Evidence from the Indian stock market. *Indian Journal of Finance*, *13*(10), 7–21. https://doi.org/10.17010/ijf/2019/v13i10/147744

Peri, M., Baldi, L., & Vandone, D. (2013). Price discovery in commodity markets. *Applied Economics Letters*, *20*(4), 397–403. https://doi.org/10.1080/13504851.2012.709590

Perumandla, S., & Kurisetti, P. (2018). Time - varying correlations, causality, and volatility linkages of Indian commodity and equity markets: Evidence from DCC - GARCH. *Indian Journal of Finance*, *12*(9), 21–40. https://doi.org/10.17010/ijf/2018/v12i9/131558

Purohit, H., Bodhanwala, S., & Choudhary, N. (2015). Empirical study on price discovery role in non-precious metals market in India. *SAMVAD: SIBM Pune Research Journal, 10*, 15–25. https://samvad.sibmpune.edu.in/index.php/samvad/article/view/98321/71458

Quandt, R. E. (1960). Tests of the hypothesis that a linear regression system obeys two separate regimes. *Journal of the American Statistical Association*, *55*(290), 324–330. https://doi.org/10.1080/01621459.1960.10482067

Rani, P., & Kumar, S. (2023). Agricultural commodities' research associated with economic activities in the past 20 years: A bibliometric analysis. *Indian Journal of Research in Capital Markets, 10*(3–4), 40–61. https://doi.org/10.17010/ijrcm/2023/v10i3-4/173430

Sehgal, S., Rajput, N., & Diesting, F. (2013). *Price discovery and volatility spillover: Evidence from Indian commodity markets*. Available at SSRN. https://ssrn.com/abstract=2149790

Seth, N., & Sidhu, A. (2021). Price discovery and volatility spillover for Indian energy futures market in the pre- and post-crisis periods. *Indian Journal of Finance*, *15*(8), 24–39. https://doi.org/10.17010/ijf/2021/v15i8/165816

Sonia. (2023). Indian commodity derivatives market: A performance review. *Indian Journal of Research in Capital Markets, 10*(2), 20–29. https://doi.org/10.17010/ijrcm/2023/v10i2/173302

Zarei, A., Ariff, M., Hook, L. S., & Nassir, A. M. (2015). Identifying multiple structural breaks in exchange rate series in a finance research. *Pertanika Journal of Social Sciences and Humanities*, *23*(S), Article ID JSSH-S0026-2015. http://www.pertanika.upm.edu.my/pjssh/browse/special-issue?article=JSSH-S0026-2015

About the Authors

U. Sarita Singha, currently a Research Scholar at NIT Silchar, focuses her research on the Indian commodity market, financial derivatives, the Indian financial system, and commodity derivatives. She has made notable contributions to her field, including the publication of a research paper in a reputed journal.

Professor N. B. Singh is a distinguished Professor of Economics at NIT Silchar, bringing over 18 years of dedicated teaching and research experience to the field. In the course of his distinguished career, he has successfully mentored four Ph.D. candidates, advancing the intellectual development of upcoming economists. Several highly acclaimed research pieces that have been published in esteemed journals are among his scholarly accomplishments. Furthermore, he has made noteworthy advances in his field of study, having finished a large-scale sponsored research project that has further cemented his standing as a preeminent authority.

Kelvin Mutum is an Assistant Professor at NIT Meghalaya, boasting over 7 years of combined industry and academic experience. His areas of interest in the study include financial engineering, behavioral finance, financial derivatives, and the Indian financial system. With a large number of research papers published in reputable journals, he has an exceptional portfolio that demonstrates his skill and commitment to furthering knowledge in these fields.