

The lead–lag relationship between spot and futures prices: Empirical evidence from the Indian commodity market

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Highlights

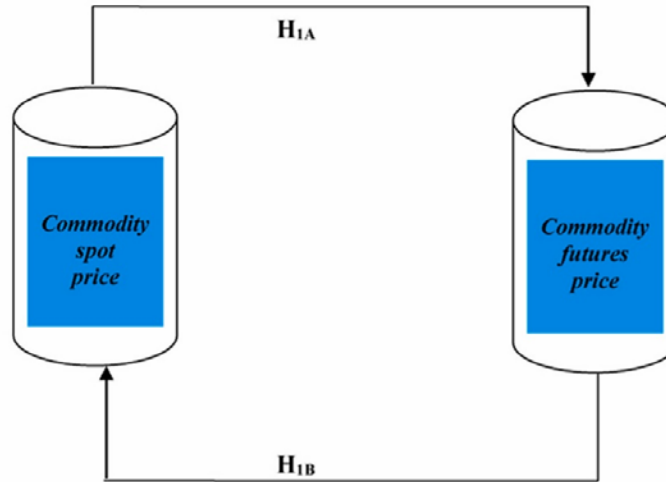
- The study investigates linkage between spot and futures prices in the Indian commodity market during 2009–2020.
- Six commodities and three indices are used for the empirical process by deploying an autoregressive distributive lag model.
- There is a long-run equilibrium relationship between the spot and futures prices of the six selected commodities.
- The long-run results reveal unidirectional causality from the spot to the futures price.
- The short-run results show both bidirectional and unidirectional causality between the two prices.

Abstract

This paper examines the relationship between spot and futures prices in the Indian commodity market for the period 2009 to 2020. The ARDL bounds-testing technique is used to explore the long-run relationship between these two prices. A vector error correction model is then used to reveal the nature of Granger causality between the two. Six commodities, namely aluminum, copper, crude oil, gold, nickel, and silver, and three indices, namely agricultural, livestock, and precious metals, are used for this empirical process. The results indicate a long-run equilibrium relationship between the spot and futures prices of these commodities. The causality analysis reveals unidirectional causality in the long run from the spot to the futures price for aluminum and copper, and both bidirectional and unidirectional causality in the short run between the two prices for aluminum, copper, gold, and silver.

Graphical abstract

H_{1A} : Commodity spot price Granger-causes commodity futures price
 H_{1B} : Commodity futures price Granger-causes commodity spot price.



Note:

H_{1A} : Commodity spot price Granger-causes commodity futures price

H_{1B} : Commodity futures price Granger-causes commodity spot price

Keywords: Spot price; Futures price; ARDL; VECM; Commodity market; India

1. Introduction

In a perfect financial market, new information would immediately be reflected in market prices, in line with the efficient market hypothesis (Fama, 1970). Accordingly, relevant information would instantaneously be reflected in the spot and futures market without any leading or lagging movements in one or the other (Abhyankar, 1995; Bekiros and Diks, 2008; Debasish, 2009; Jiang et al., 2019; Kang et al., 2006), which means that there would be no arbitrage or speculation opportunity (Huth and Abergel, 2014; Kavussanos et al., 2008; Wahab and Lashgari, 1993). One way to investigate whether a market is well developed is therefore to investigate the lead–lag relationship between spot and futures markets (see Brooks et al., 2001; Kang et al., 2006; Kawaller et al., 1987; Shyy et al., 1996; Tse, 1995). If the lead–lag relationship is sufficiently short, the market is considered to be well developed and efficient. Allen and Gale (1997) found that financial systems deal with non-diversifiable risk differently. Ang (2008) and Chang and Caudill (2005) recognized that the results of studies on financial data can differ due to institutional and structural differences between countries or economies.

One of the aims of this article is to determine if, and to what extent, the Indian commodity market is efficient. India is a developing market economy. It is the world's fifth largest economy by nominal gross domestic product (GDP) and the third largest by purchasing power parity (PPP). One of the characteristics of India as a developing economy is that it is mainly primary producing, i.e. the majority of the population (52%) are engaged in agriculture. Moreover, the best commodities to trade in India are crude oil, aluminum, copper, gold, and silver. This study will use, in its empirical analysis, the futures and spot prices of six commodities, namely aluminum, copper, crude oil, gold, nickel, and silver, and three indices, namely the agricultural, livestock, and precious metals, for the Indian market.

Numerous studies have been conducted to explore the lead–lag relationship between various market indicators. Most of these originated in developed economies and indicate that futures markets tend to lead spot markets (see Abhyankar, 1995; Asche and Guttormsen, 2002; Brooks et al., 2001; Chan, 1992; Chen et al., 2017; Da Fonseca and Zaatour, 2017; Finnerty and Park, 1987; Ghosh, 1993; Grünbichler et al., 1994; Harris, 1989; Huth and Abergel, 2014; Kawaller et al., 1987; Martikainen and Puttonen, 1992; Shyy et al., 1996; Stoll and Whaley, 1990; Tang et al., 1992; Tse, 1995; Tse and Chan, 2010; Zhang and Liu, 2018). However, there has been an increase in studies in emerging economies, most of which have also found that futures markets tend to lead spot markets (see Choudhary and Bajaj, 2012; Debasish and Mishra, 2008; Demir et al., 2019; Floros and Vougas, 2007; Gong et al., 2016; Jiang et al., 2019; Kavussanos et al., 2008).

A better understanding of the flow of information between markets leads to improvements in investment strategies, economic policy, asset valuation, and hedging performance (Alemany et al., 2020). To help provide a better understanding of lead–lag dynamics in an emerging economy, this article investigates lead–lag relationships in the Indian commodity market, especially with reference to the nexus between spot and futures prices. The aim is to present a means to evaluate the stage of development of an emerging economy's financial market by looking at the current level of market efficiency. This study deviates from previous studies on the lead–lag relationship and makes a novel contribution to the literature on the topic. It looks at the direction of lead–lag relationships in four instances, namely (1) from the spot to the futures market, (2) from the futures to the spot market, (3) from the spot to the futures market and vice versa, and (4) with the spot and futures markets operating independently of each other.

The findings presented in this article are relevant to financial market practitioners, financial economists, and academics. First, the results indicate to financial market practitioners how to find and exploit profitable opportunities that arise from econometric forecasts. Second, the study adds value for financial economists in terms of testing the validity of financial market theories such as the efficient market hypothesis. Third, the research may be of interest to academics, investors, and others who are interested in financial market development and differences between developed and emerging economies in this regard.

The remainder of the paper is organized as follows: a comprehensive literature review is presented in Section 2, the data and model are described in Section 3, the econometric analysis and empirical results are discussed in Section 4, and a conclusion is given in Section 5.

2. Literature review

The seminal papers of Bhattacharya (1987) and Kawaller et al. (1987) set a benchmark for research on lead–lag relationships between spot and futures prices and between other market factors and even entire markets. In the years since, there have been numerous studies to investigate this relationship, with the most recent study conducted by Alemany et al. (2020). The context and aim of research on lead–lag relationships vary widely.

Earlier studies looked at the theory behind lead–lag relationships, the presence and extent of lead–lag relationships, and the statistical methodology used for measuring lead–lag relationships. Most of these studies used spot and futures returns from commodity markets, although some explored lead–lag relationships between exchange rates (Basnarkov et al., 2020), futures speculation types (i.e. short-run, long-run, and excessive) and price volatility (Algieri and Leccadito, 2019), daily sovereign credit default swap spread changes (Bouri et al., 2019), liquid and illiquid indices (Chaibi, 2014), electricity market spot and futures prices (Da Silva et al., 2019), Eurozone business cycles (Duran and Ferreira-Lopes, 2017), lean hogs and pork bellies (Jackline and Deo, 2011), soybean bases of different regions (Kurfman, 2011), interest rates (McLeod, 2008), leader and follower stocks (Rusmanto et al., 2016; Xia et al., 2018), credit default swaps and stock markets (Shahzad et al., 2017), credit and housing markets (Shen et al., 2016), oil and agricultural markets (Tiwari et al., 2018), volatility and trading volume (Todorova and Clements, 2018), bonds and the underlying stocks (Tolikas, 2018), BRIC countries' stock exchanges (Tonin et al., 2013), and the returns of different metals (Tweneboah and Alagidede, 2018). Most of the studies used daily data, although some data was presented in intervals of seconds, minutes, 5 min, hours, etc.

In the past, studies on lead–lag relationships were conducted mostly in developed economies, with the United States of America being the preferred source of data. More recently, there has been an increase in studies conducted in emerging economies such as Turkey (Basdas, 2009), China (Demir et al., 2019; Gong et al., 2016; Jiang et al., 2019; Ren et al., 2019; Wang et al., 2013), Greece (Floros and Vougas, 2007; Kavussanos et al., 2008), India (Choudhary and Bajaj, 2012; Debasish, 2009; Debasish and Mishra, 2008; Jackline and Deo, 2011), Indonesia (Rusmanto et al., 2016), Korea (Kang et al., 2006; Kim et al., 2009), Malaysia (Taunson et al., 2018), and Thailand (Judge and Reancharoen, 2014). However, there are still very few studies on lead–lag relationships in emerging economies. Because of the growth potential of emerging economies and its dependency on foreign investment, it is imperative to continue conducting research in this domain to better understand how emerging markets operate and to find ways to ensure that efforts are made to reduce lead–lag relationships so as to facilitate an efficient market.

Most earlier studies on lead–lag relationships used methods such as regression, cointegration tests, multivariate vector error correction models, Granger causality, and generalized autoregressive conditional heteroskedasticity (GARCH). However, a number of studies have made methodological contributions by measuring such relationships using novel techniques such as thermal optimal path analysis (Jiang et al., 2019; Ren et al., 2019; Shao et al., 2019; Yang and Shao, 2020), the Hayashi–Yoshida cross-correlation estimator (Huth and Abergel, 2014), synchronous correlation networks (Curme et al., 2015), the Hawkes model (Da Fonseca and Zaatour, 2017), the multi-asset lagged adjustment model

(Buccheri et al., 2020), and wavelet multiple correlations and cross-correlations (Tweneboah and Alagidede, 2018). Basdas (2009) used an error correction model (ECM) with cost of carry (COC), autoregressive integrated moving average (ARIMA), and vector autoregression (VAR) on the same dataset to observe differences in the results obtained.

The present study will use the autoregressive distributed lag (ARDL) technique (see Pesaran et al., 2001), which is discussed in Section 3.5.

3. Research method

In this section, the analytical framework of the lead–lag relationship, data sources, variables, descriptive statistics, and statistical models are discussed.

3.1. Analytical framework of lead–lag relationship

Theoretically, the relationship between a futures price and the underlying spot (or asset) price leads to the so-called cost of carry model (Brooks et al., 2001; Stoll and Whaley, 1990; Tse, 1995). It is given by the following equation:

$$F_t = S_t e^{(r-d)(T-t)} \quad (1)$$

where F_t is the futures price at time t , S_t is the spot price at time t , r is the risk-free rate of return, d is the dividend yield, and T is the futures contract maturity date. Adapting the equation, we get

$$F_t = S_t + (r - d) \quad (2)$$

where $F_t = \ln \left(\frac{F_t}{F_{t-1}} \right)$ and $S_t = \ln \left(\frac{S_t}{S_{t-1}} \right)$

Equation (2) implies that, in an efficient market, spot and futures returns should be related and one return should not lead the other. However, markets are not efficient and there usually is a lead–lag effect between spot and futures prices (Brooks et al., 2001). The relationship between spot and futures markets can take one or more of four directions:

- Unidirectional from the spot to the futures market: the supply-leading hypothesis (SLH)
- Unidirectional from the futures to the spot market: the demand-following hypothesis (DFH)
- Bidirectional from the spot to the futures market and from the futures to the spot market: the feedback hypothesis (FBH)
- Neutral, which means that the spot and futures markets are independent of each other: the neutrality hypothesis (NLH)

3.2. Data sources and variables

The present study investigates the relationship between the spot and futures prices of various commodities and indices in the Indian commodity market, employing daily data from 2009 to 2020 obtained from the *Bloomberg Database*. This period is selected based on the availability of complete and up-to-date data, especially after the effect of the global financial crisis (GFC) from 2008 to 2009. The futures and spot prices of six commodities, namely aluminum (FAL & SAL), copper (FCO & SCO), crude oil (FCR & SCR), gold (FGO & SGO), nickel (FNI & SNI), and silver (FSI & SSI), and three indices, namely agricultural (FAI & SAI), livestock (FLS & SLS), and precious metals (FPM & SPM), were chosen for this study. All the variables were converted into their natural logarithms for the analysis.

Table 1. Descriptive statistics of variables.

Variables	S1	S2	S3	S4	S5	S6	S7	S8
FAL	0.294	0.292	0.444	0.156	0.057	0.054	2.764	7.725*
SAL	0.292	0.293	0.444	0.153	0.058	0.011	2.759	6.737*
FCO	2.478	2.484	2.665	2.288	0.081	-0.098	2.632	18.67*
SCO	3.821	3.829	4.008	3.636	0.079	-0.085	2.621	18.61*
FCR	1.836	1.837	2.057	1.418	0.139	-0.263	1.934	146.81*
SCR	1.836	1.884	2.057	1.418	0.141	-0.271	1.956	143.91*
FGO	3.153	3.165	3.224	3.104	0.032	-0.816	1.650	22.21*
SGO	2.746	2.754	2.808	2.698	0.029	-0.172	1.706	20.32*
FNI	4.165	4.157	4.467	3.879	0.129	0.086	2.282	58.54*
SNI	4.165	4.156	4.467	3.879	0.129	0.086	2.282	58.64*
FSI	1.303	1.251	1.686	1.136	0.128	0.939	2.647	395.9*
SSI	1.304	1.253	1.685	1.136	0.127	0.940	2.648	397.4*
FAI	2.092	2.074	2.293	1.891	0.107	0.054	1.871	137.8*
SAI	2.468	2.431	2.652	2.352	0.080	0.730	2.121	310.7*
FLS	1.821	1.830	1.923	1.667	0.050	-0.285	2.410	72.13*
SLS	2.242	2.246	2.396	2.082	0.055	0.127	3.121	8.473*
FPM	2.584	2.558	2.790	2.462	0.075	0.860	2.572	336.3*
SPM	2.606	2.582	2.799	2.485	0.070	0.785	2.571	283.8*

Note 1: FAL is aluminum futures price, SAL is aluminum spot price, FCO is copper futures price, SCO is copper spot price, FCR is crude oil futures price, SCR is crude oil spot price, FGO is gold futures price, SGO is gold spot price, FNI is nickel futures price, SNI is nickel spot price, FSI is silver futures price, SSI is silver spot price, FAI is futures price of agricultural index, SAI is spot price of agricultural index, FLS is futures price of livestock index, SLS is spot price of livestock index, FPM is futures price of precious materials, and SPM is spot price of precious metals.

Note 2: S1 is mean, S2 is median, S3 is maximum, S4 is minimum, S5 is standard deviation, S6 is skewness, S7 is kurtosis, and S8 is Jarque–Bera statistics.

Note 3: * denotes statistical significance at the 1% level.

3.3. Descriptive statistics

The descriptive statistics for all the variables are presented in Table 1. The mean value of FAL is 0.294, with maximum and minimum values of 0.444 and 0.156 respectively, while the mean value of SAL is 0.292, with maximum and minimum values of 0.444 and 0.153 respectively. The mean value of both FNI and SNI is 4.165, the highest among the commodities and indices, with maximum and minimum values of 4.467 and 3.879 respectively. FCR and SCR have the highest standard deviation, followed by FNI and SNI, suggesting the high volatility of crude oil and nickel compared to the other commodities and indices. Except for FCO, SCO, FCR, SCR, FGO, and SGO, all the variables are positively skewed. The kurtosis values are all positive and in the range of less than 3, which indicates that the variables are nearly normal and mesokurtic. These results are well supported by Jarque–Bera statistics (see Table 1).

3.4. Model specification

The main objective of the present study is to examine the lead–lag relationship between spot and futures markets in India's emerging economy to determine how efficient the market is. The smaller the lead–lag relationship between the futures and spot prices, the better developed and more efficient the market. According to the efficient market hypothesis, information is reflected instantly in spot and futures prices in an efficient market, which means that there is no lead or lag effect. It thus follows that a small lead–lag effect between spot and futures prices shows a well-developed, efficient market.

Equation (3) was used to examine the relationship between the spot and futures markets of the six commodities and three indices mentioned earlier:

$$SCP_t = \alpha + \beta FCP_t + \varepsilon_i \quad (3)$$

where, SCP is a proxy for the spot price of commodities and indices and FCP is a proxy for the futures price of commodities and indices. Bidirectional causality is expected between these two prices for all the commodities and indices being investigated.

3.5. Cointegration – ARDL bounds-testing procedure

The present study relies on ARDL technique (see Pesaran et al., 2001) for examining the long- and short-run dynamic bidirectional causality between spot and futures prices in the Indian commodity market. This technique is preferred to cointegration methods such as the Engle-Granger approach and the Johansen and Juselius test. First, where the underlying variables are stationary at level I(0), first difference I(1), or both, the ARDL technique is preferred. Second, variables can take a different number of lags under the ARDL model. Third, it is the perfect model for small sample size studies. Fourth, the ARDL gives unbiased long-run estimates. Fifth, the error correction term from the ARDL can be derived easily through simple linear transformation (see Banerjee et al., 1993). In analyzing the long-run association and the short-run dynamics of the variables, the ARDL unrestricted error correction model (UECM) is expressed as follows:

$$\Delta \ln SCP_t = \alpha_0 + \sum_{i=1}^p \alpha_1 \Delta \ln SCP_{t-i} + \sum_{i=1}^q \alpha_2 \Delta \ln FCP_{t-i} + \eta_1 \ln SCP_{t-i} + \eta_2 \ln FCP_{t-i} + \zeta_t \quad (4)$$

where Δ is the difference operator, ζ_t is the white noise error term, and p and q represent the lag period of the explained variable and each explanatory variable respectively. SCP is a proxy for the commodity spot price, and FCP is a proxy for the commodity futures price.

Equation (4) is a UECM that corresponds to ARDL bound tests, where $\Delta \ln SCP$ and $\Delta \ln FCP$ represent their respective difference values, α coefficients represent short-term dynamic relationships, and η coefficients represent long-run dynamic relationships.

ARDL bound tests use the Wald or F-statistic for a joined significance test to determine if there is a cointegration relationship (see Pesaran et al., 2001). The null hypothesis of this test is $H_0: \eta_1 = \eta_2 = 0$, which means that there is no cointegration relationship. The alternative hypothesis is $H_1: \eta_1 \neq \eta_2 \neq 0$, which means that there is a cointegration relationship. The two critical bounds, namely the upper bound $I(1)$ and lower bound $I(0)$, are used to test for cointegration. F-statistics that exceed the upper critical bound $I(1)$ indicate the rejection of the null hypothesis and reveal a long-run relationship. On the other hand, F-statistics that are less than the lower bound critical value $I(0)$ indicate the acceptance of the null hypothesis and depict no cointegration (i.e. no long-run relationship). An inclusive result is obtained when F-statistics lie between the upper and lower critical bounds. The estimation of the ARDL is very sensitive to lag length. Both AIC and SBC criteria are used to choose the optimum lag length. The next step is to compute the long-run and short-run results and to perform the diagnostic tests to ensure model stability.

3.6. VECM procedure

After examining the long-run relationship between the spot and futures prices of the commodities, the Granger causality test is used to examine the causality between the two. If there is cointegration between the spot and futures prices, the following vector error correction model (VECM) can be used:

$$\Delta SCP_t = \alpha_{10} + \sum_{k=1}^p \alpha_{11} \Delta SCP_{t-k} + \sum_{k=1}^q \alpha_{12} \Delta FCP_{t-k} + \mu_1 ECT_{t-1} + \varepsilon_{1t} \quad (5)$$

$$\Delta FCP_t = \alpha_{20} + \sum_{k=1}^p \alpha_{21} \Delta FCP_{t-k} + \sum_{k=1}^q \alpha_{22} \Delta SCP_{t-k} + \mu_2 ECT_{t-1} + \varepsilon_{2t} \quad (6)$$

where Δ is the difference operator and ECT_{t-1} is the lagged error correction term, derived from the cointegrating equations, i.e. from the long-run association. The coefficients of ECT_{t-1} (i.e., μ_1 and μ_2) represent the long-run equilibrium speed of adjustment after the shock in the short run. The long-run causality is found by the significance of the coefficient of the error correction terms (ECTs) using the t-statistics. A significant relationship in first differences of the variables indicates the direction of short-run causality. The joint χ^2 statistic of the first difference lagged independent variables is used to test the direction of short-run causality between the variables. For instance, $\alpha_{11} \neq 0$ shows that the commodity futures price Granger-causes the commodity spot price, while $\alpha_{12} \neq 0$ shows that the commodity spot price Granger-causes the commodity futures price.

4. Results and discussion

4.1. Unit root tests

Before examining potential long-run relationships between spot and futures prices, one must establish the order of integration among the variables. This study uses the augmented Dickey–Fuller (ADF) test (see Dickey and Fuller, 1979), the Phillips–Perron (PP) test (see Phillips and Perron, 1988), and the Andrew–Zivot (AZ) test (see Zivot and Andrews, 1992), as indicated in Table 2, Table 3, respectively. The test is conducted at both level $I(0)$ and first difference $I(1)$. The results from all the tests indicate that the futures and spot prices of all the selected commodities and indices are non-stationary at level data, but that the variables are all stationary at 1% when tested at first difference.

Table 2. Unit root test statistics of variables.

Variables	ADF statistics			PP statistics		
	LD	FD	Order	LD	FD	Order
<i>FAL</i>	−0.162	−54.3*	$I(1)$	−0.162	−54.3*	$I(1)$
<i>SAL</i>	−0.268	−57.3*	$I(1)$	−0.297	−57.3*	$I(1)$
<i>FCO</i>	0.196	−51.30*	$I(1)$	0.2022	−51.32*	$I(1)$
<i>SCO</i>	0.247	−52.35*	$I(1)$	0.262	−52.38*	$I(1)$
<i>FCR</i>	0.363	−54.70*	$I(1)$	0.366	−54.54*	$I(1)$
<i>SCR</i>	0.351	−53.88*	$I(1)$	0.361	−53.76*	$I(1)$
<i>FGO</i>	−2.014	−15.87*	$I(1)$	−1.961	−15.87*	$I(1)$
<i>SGO</i>	−1.763	−15.88*	$I(1)$	−1.724	−15.88*	$I(1)$
<i>FNI</i>	0.249	−51.45*	$I(1)$	0.261	−51.48*	$I(1)$
<i>SNI</i>	0.250	−51.45*	$I(1)$	0.261	−51.48*	$I(1)$
<i>FSI</i>	−0.235	−52.76*	$I(1)$	−0.233	−52.76*	$I(1)$
<i>SSI</i>	−0.208	−50.16*	$I(1)$	−0.211	−50.18*	$I(1)$
<i>FAI</i>	0.679	−48.46*	$I(1)$	0.654	−48.46*	$I(1)$
<i>SAI</i>	0.035	−49.31*	$I(1)$	0.033	−49.31*	$I(1)$
<i>FLS</i>	0.496	−50.34*	$I(1)$	0.496	−50.34*	$I(1)$
<i>SLS</i>	−0.480	−48.79*	$I(1)$	−0.447	−48.96*	$I(1)$
<i>FPM</i>	−0.449	−52.42*	$I(1)$	−0.460	−52.42*	$I(1)$
<i>SPM</i>	−0.577	−53.01*	$I(1)$	−0.598	−53.02*	$I(1)$

Note 1: *FAL* is aluminum futures price, *SAL* is aluminum spot price, *FCO* is copper futures price, *SCO* is copper spot price, *FCR* is crude oil futures price, *SCR* is crude oil spot price, *FGO* is gold futures price, *SGO* is gold spot price, *FNI* is nickel futures price, *SNI* is nickel spot price, *FSI* is silver futures price, *SSI* is silver spot price, *FAI* is futures price of agricultural index, *SAI* is spot price of agricultural index, *FLS* is futures price of livestock index, *SLS* is spot price of livestock index, *FPM* is futures price of precious materials, and *SPM* is spot price of precious metals.

Note 2: ADF is augmented Dickey–Fuller test, PP is Phillips–Perron test, LD is level data, FD is first difference data, and $I(1)$ is integrated of order.

Note 3: * denotes statistical significance at the 1% level.

Table 3. Break-point statistics of variables.

Variables	t-statistics	Break date	Possible reasons for the break
<i>FAL</i>	-9.371*	02.05.2011	Industrial and service sector growth
<i>SAL</i>	-10.52*	02.05.2011	Industrial and service sector growth
<i>FCO</i>	-5.719*	14.02.2011	Industrial and service sector growth
<i>SCO</i>	-5.955*	14.02.2011	Industrial and service sector growth
<i>FCR</i>	-5.038*	31.05.2011	Industrial and service sector growth
<i>SCR</i>	-4.958*	31.05.2011	Industrial and service sector growth
<i>FGO</i>	-4.959*	02.05.2011	Industrial and service sector growth
<i>SGO</i>	-3.390*	02.05.2011	Industrial and service sector growth
<i>FNI</i>	-6.452*	03.04.2011	Industrial and service sector growth
<i>SNI</i>	-2.861**	03.04.2011	Industrial and service sector growth
<i>FSI</i>	-11.27*	26.04.2011	Industrial and service sector growth
<i>SSI</i>	-8.359*	26.04.2011	Industrial and service sector growth
<i>FAI</i>	-5.561*	27.12.2013	Industrial and service sector growth
<i>SAI</i>	-5.671*	27.12.2013	Industrial and service sector growth
<i>FLS</i>	-3.718*	28.03.2013	Industrial and service sector growth
<i>SLS</i>	-5.595**	28.03.2013	Industrial and service sector growth
<i>FPM</i>	-8.186*	12.11.2009	Industrial and service sector growth
<i>SPM</i>	-8.096*	12.11.2009	Industrial and service sector growth

Note 1: *FAL* is aluminum futures price, *SAL* is aluminum spot price, *FCO* is copper futures price, *SCO* is copper spot price, *FCR* is crude oil futures price, *SCR* is crude oil spot price, *FGO* is gold futures price, *SGO* is gold spot price, *FNI* is nickel futures price, *SNI* is nickel spot price, *FSI* is silver futures price, *SSI* is silver spot price, *FAI* is futures price of agricultural index, *SAI* is spot price of agricultural index, *FLS* is futures price of livestock index, *SLS* is spot price of livestock index, *FPM* is futures price of precious materials, and *SPM* is spot price of precious metals.

Note 2: * and ** denote statistical significance at the 1% and 5% levels respectively.

4.2. Bounds-testing for cointegration

Bounds-testing analysis is used to examine the long-run connections between spot and futures prices. As shown in Table 4, the bounds-testing results for the present study indicate that the estimated F-statistics exceed the upper critical bound for all six commodities and for one of the indices. Hence, the null hypothesis of no cointegration is rejected. There may be a long-run relationship between the spot and futures prices of the six commodities and the agricultural index. However, for the livestock and materials indices, the estimated F-statistics are lower than the lower critical bound. Thus, the null hypothesis of no cointegration between spot and futures prices cannot be rejected here (see Table 4).

Table 4. ARDL bounds-testing results.

Estimated models	Optimal lag length	F statistics	Diagnostic tests		Critical values at 1%, 5% & 10%	
			χ^2_A	χ^2_S	I(0) bound	I(1) bound
<i>F (FAL/SAL)</i>	4, 4	66.31*	704.6*	43.11*	6.84/4.94/4.04	7.84/5.73/4.78
<i>F (SAL/FAL)</i>	3, 3	52.26*	211.1*	30.54*	6.84/4.94/4.04	7.84/5.73/4.78
<i>FCO</i>	4, 4	24.31*	91.60*	13.01*	6.84/4.94/4.04	7.84/5.73/4.78
<i>SCO</i>	4, 4	19.89*	54.09*	15.06*	6.84/4.94/4.04	7.84/5.73/4.78
<i>FCR</i>	4, 4	223.6*	55.85*	6.501*	6.84/4.94/4.04	7.84/5.73/4.78
<i>SCR</i>	4, 4	2.222***	59.38*	6.153*	6.84/4.94/4.04	7.84/5.73/4.78
<i>FGO</i>	4, 4	2.269***	4.349**	11.47*	6.84/4.94/4.04	7.84/5.73/4.78
<i>SGO</i>	4, 4	2.582*	5.643**	13.03*	6.84/4.94/4.04	7.84/5.73/4.78
<i>FNI</i>	2, 3	147.4*	79.04*	3.519*	6.84/4.94/4.04	7.84/5.73/4.78
<i>SNI</i>	3, 2	147.7*	78.85*	3.501*	6.84/4.94/4.04	7.84/5.73/4.78
<i>FSI</i>	2, 2	538.5*	18.71*	2.318*	6.84/4.94/4.04	7.84/5.73/4.78
<i>SSI</i>	3, 3	333.3*	11.51*	6.500*	6.84/4.94/4.04	7.84/5.73/4.78
<i>FAI</i>	4, 4	4.963**	9.575*	5.287*	6.84/4.94/4.04	7.84/5.73/4.78
<i>SAI</i>	4, 4	4.296**	9.507**	5.562*	6.84/4.94/4.04	7.84/5.73/4.78
<i>FLS</i>	4, 4	0.205	5.767*	2.334*	6.84/4.94/4.04	7.84/5.73/4.78
<i>SLS</i>	4, 4	0.128	5.770*	2.541*	6.84/4.94/4.04	7.84/5.73/4.78
<i>FPM</i>	4, 4	0.558	19.14*	51.28*	6.84/4.94/4.04	7.84/5.73/4.78
<i>SPM</i>	4, 4	0.647	11.51*	19.68*	6.84/4.94/4.04	7.84/5.73/4.78

Note 1: FAL is aluminum futures price, SAL is aluminum spot price, FCO is copper futures price, SCO is copper spot price, FCR is crude oil futures price, SCR is crude oil spot price, FGO is gold futures price, SGO is gold spot price, FNI is nickel futures price, SNI is nickel spot price, FSI is silver futures price, SSI is silver spot price, FAI is futures price of agricultural index, SAI is spot price of agricultural index, FLS is futures price of livestock index, SLS is spot price of livestock index, FPM is futures price of precious materials, and SPM is spot price of precious metals.

Note 1: χ^2_A is heteroscedasticity ARCH test; and χ^2_S is Breusch–Godfrey serial correlation LM test.

Note 2: *, ** and *** denote statistical significance at the 1%, 5%, and 10% levels respectively.

On the basis of the unit root results, all the variables were found to be between I(0) and I(1). Thus, the ARDL technique is the most appropriate.¹ However, to check the robustness of the ARDL results, the Johansen and Juselius cointegration test, which uses two statistical measures, namely maximum eigenvalues and trace statistics, had to be used. The results of both these tests are reported in Table 5. The results show cointegrating vectors between the spot and futures prices. Therefore, the spot and future commodity prices are cointegrated, which suggests a long-run equilibrium between the commodity spot and futures prices. This finding is supported by the ARDL bounds-testing results.

Table 5. Results of Johansen and Juselius cointegration test.

Pairs of commodities	Hypothesized no. of cointegrating vectors	Trace statistics	Max. eigenvalue statistics	No. of cointegrating vectors
FAL & SAL	None ($k \leq 0$)	111.1*	106.1*	2
	At most 1 ($k \leq 1$)	4.999**	4.999**	
FCO & SCO	None ($k \leq 0$)	46.31*	42.52*	1
	At most 1 ($k \leq 1$)	3.791	3.791	
FCR & SCR	None ($k \leq 0$)	406.3*	403.8*	1
	At most 1 ($k \leq 1$)	2.469	2.469	
FGO & SGO	None ($k \leq 0$)	20.48**	16.71**	1
	At most 1 ($k \leq 1$)	5.672	5.672	
FNI & SNI	None ($k \leq 0$)	256.5*	254.1*	1
	At most 1 ($k \leq 1$)	2.391	2.391	
FSI & SSI	None ($k \leq 0$)	366.0*	363.9*	1
	At most 1 ($k \leq 1$)	2.159	2.159	
FAI & SAI	None ($k \leq 0$)	16.70**	14.71***	1
	At most 1 ($k \leq 1$)	2.989	2.989	
FLS & SLS	None ($k \leq 0$)	7.198	7.115	0
	At most 1 ($k \leq 1$)	0.083	0.083	
FPM & SPM	None ($k \leq 0$)	3.710	2.850	0
	At most 1 ($k \leq 1$)	0.860	0.860	

Note 1: FAL is aluminum futures price, SAL is aluminum spot price, FCO is copper futures price, SCO is copper spot price, FCR is crude oil futures price, SCR is crude oil spot price, FGO is gold futures price, SGO is gold spot price, FNI is nickel futures price, SNI is nickel spot price, FSI is silver futures price, SSI is silver spot price, FAI is futures price of agricultural index, SAI is spot price of agricultural index, FLS is futures price of livestock index, SLS is spot price of livestock index, FPM is futures price of precious materials, and SPM is spot price of precious metals.

Note 2: k is cointegrating vector.

Note 3: *, ** and *** denote statistical significance at the 1%, 5%, and 10% levels respectively.

Again to complement the ARDL results, the parameter stability was tested using cumulative sum (CUSUM) and cumulative sum squares (CUSUMSQ). The CUSUM test uses cumulative sum recursive residuals based on the observations and is updated recursively and plotted against any structural break points. In contrast, the CUSUMSQ test uses squared recursive residuals and follows the same procedure. That means the CUSUM test can be used even when the structural break points are unknown. If the plot of the CUSUM and CUSUMSQ stays within the 5% critical bound, then the null hypothesis that all coefficients are stable cannot be rejected. The null hypothesis can be rejected, however, if either of the parallel lines is crossed. From the figures of the CUSUM and the CUSUMSQ plots, it is clear that the parameters of the model (between the commodity spot and futures prices) do not suffer from any structural instability over the period considered in this study. The results of the CUSUM and CUSUMSQ tests are not given here but can be obtained from the authors.

Table 6. Results of panel Granger causality test.

Dependent variables	Independent variables		Inferences	ECT-1 coefficient
	(possible sources of causation)	(possible long-run causality)		
	ΔFAL	SAL	ECT_{-1}	
ΔFAL	—	227.0*	-0.132/-8.146*	$SAL \leftrightarrow FAL$
ΔSAL	15.08*	—	-0.104/-0.052	
	ΔFCO	ΔSCO	ECT_{-1}	
ΔFCO	—	17.15*	-0.122/-3.378*	$SCO \leftrightarrow FCO$
ΔSCO	46.39*	—	-0.039/-1.069	
	ΔFCR	ΔSCR	ECT_{-1}	
ΔFCR	—	0.074	-0.241/-2.670	$SCR \nmid FCR$
ΔSCR	1.272	—	-0.153/-0.168	
	ΔFGO	ΔSGO	ECT_{-1}	
ΔFGO	—	2.233	-0.011/-0.129	$SGO \leftarrow FGO$
ΔSGO	12.79*	—	-0.082/-0.961	
	ΔFNI	ΔSNI	ECT_{-1}	
ΔFNI	—	3.649	-0.581/-0.876	$SNI \nmid FNI$
ΔSNI	3.464	—	-0.796/-1.200	
	ΔFSI	ΔSSI	ECT_{-1}	
ΔFSI	—	26.9*	-0.69/-6.69*	$SSI \leftrightarrow FSI$
ΔSSI	40.38*	—	-0.19/-1.98	
	ΔFAI	ΔSAI	ECT_{-1}	
ΔFAI	—	2.407	-0.001/-1.758	$SAI \leftarrow FAI$
ΔSAI	13.64*	—	-0.001/-1.106	
	ΔFLS	ΔSLS	ECT_{-1}	
ΔFLS	—	0.237	---/---	$SLS \leftarrow FLS$
ΔSLS	25.91*	—	---/---	
	ΔFPM	ΔSPM	ECT_{-1}	
ΔFPM	—	2.162	---/---	$SPM \leftarrow FPM$
ΔSPM	9.331*	—	---/---	

Note 1: FAL is aluminum futures price, SAL is aluminum spot price, FCO is copper futures price, SCO is copper spot price, FCR is crude oil futures price, SCR is crude oil spot price, FGO is gold futures price, SGO is gold spot price, FNI is nickel futures price, SNI is nickel spot price, FSI is silver futures price, SSI is silver spot price, FAI is futures price of agricultural index, SAI is spot price of agricultural index, FLS is futures price of livestock index, SLS is spot price of livestock index, FPM is futures price of precious materials, and SPM is spot price of precious metals.

Note 2: ECT_{-1} is error correction term.

Note 3: For ECT_{-1} coefficient, the first value is an estimated value, while the second is t-statistics.

Note 4: * denotes statistical significance at the 1% level.

Note 5: \leftarrow , \leftrightarrow , and \nmid indicate unidirectional, bidirectional, and no Granger causality between the variables, respectively.

4.3. Long-run and short-run causality analysis

Cointegration is a necessary condition for a long-run relationship. However, to understand the causal relation between commodity spot and futures prices, the VECM procedure is followed. The VECM procedure enables the exploration of the short- and long-run dynamics of the variables in the system. Changes in both dependent and independent variables on lagged deviations are regressed here, as in equations (5), (6)). Table 6 shows the results of the VECM procedure. Based on the results obtained by means of this test, the long-run relationship is measured through error correction terms. The statistical significance of ECTs for the futures prices of aluminum and copper, as the dependent variables, indicates that these variables provide an important channel by means of which to influence the commodity market in the long run. In other cases, the ECTs are not statistically significant, which implies that the commodity spot price is insignificant in transmitting the effects of futures prices in the long run.

The short-run causality analysis has produced interesting findings. These short-run causalities shed light on the direction of causation and thus on the commodity market development mechanism taking place in the economy. Specifically for causality analysis, a block exogeneity Wald test is conducted to show the combined causality results of both the commodity spot and futures prices in the short run. The results of the analysis show the following:

1. There is bidirectional causality between the spot and futures prices for aluminum, copper, and silver, which suggests a feedback effect.
2. There is unidirectional causality from the futures to spot prices for gold and for the three indices, which suggests a supply-leading effect.
3. There is no causality between the spot and futures prices for crude oil and nickel, which suggests a neutrality effect.

4.4. GIRFs, CUSUM, and CUSUMSQ analysis

To complement these findings, generalized impulse response functions (GIRFs) were used. GIRFs trace the effect of a one-time shock to one of the innovations on the current and future values of endogenous variables. They provide insight into how shocks to commodity spot prices can affect, and are affected by, commodity futures prices. Findings obtained by means of GIRFs provide support to the causality status between spot and commodity prices in the VECM system. Additionally, due to structural changes in spot and futures prices, it is likely that these two prices may be exposed to one or more structural breaks. For this reason, the stability of both the short- and long-run coefficients that form part of the present study are verified through CUSUM and CUSUMSQ tests. Both tests are general tests for structural change in that they do not require the prior determination of structural breaks. CUSUM and CUSUMSQ tests help ensure that the estimated parameters for this study are stable over the period 2009 to 2020. The results obtained through the GIRFs, CUSUM, and CUSUMSQ tests are not included here but can be obtained from the authors.

5. Conclusion and policy implications

This study looked at the relationship between spot and futures prices in the Indian commodity market using daily data for the period 2009 to 2020. Several unit root tests, including structural break unit tests and ARDL bounds testing, were conducted to examine the integrating order of the variables and the long-run relationship between commodity spot and futures prices. The direction of causality was investigated through the VECM Granger causality approach. The robustness of the Granger causality was tested by means of GIRFs.

The unit root tests confirmed that the variables used in this study, the spot and futures prices of six commodities and three indices, are integrated of order one $I(1)$. The cointegration results confirmed that the spot and futures prices are cointegrated for the commodities and for the agricultural index. This confirms that there is a long-run relationship between spot and futures prices in the commodity market. In the long run, the causality analysis exposed unidirectional causality from the spot to the futures price for aluminum and copper only. In the short run, the causality analysis exposed bidirectional causality between the spot and futures prices for copper and silver only. That means the feedback hypothesis is found between the spot and futures prices of copper and silver. Additionally, there is unidirectional causality from the futures to spot price for gold and for the three indices. An independent relationship was observed between the spot and futures prices for nickel, which suggests a neutrality effect.

In short, the findings of this study indicate unidirectional causality from the spot to futures prices for aluminum, copper, and silver in the long-run, and bidirectional causality, unidirectional causality, and neutrality between the spot and futures prices in the short-run. The purpose of this study was to investigate, and determine the extent of, efficiency in the Indian commodity market. Based on the results of the empirical analysis, it is concluded first that the aluminum and copper commodities markets are more efficient than the other commodity markets that were investigated. The aluminum and copper commodities markets are therefore more information-efficient than the others. Second, it is deduced that, due to greater market efficiency in the aluminum and copper markets, market traders and investors cannot earn excess profits from inefficiencies in these markets. Third, however, in the case of the other commodity markets analyzed, namely crude oil, gold, nickel, and silver, it is deduced that the markets are less efficient and consequently enable traders and investors to earn excess profits, especially in the long run. The analysis of the Indian commodity markets and the lead-lag relationships observed in the agricultural index lead to a better understanding of the pricing mechanisms and possible interactions and information flows in these markets.

The Granger causality results for the short and long run indicate a need for different trading strategies for short and long runs in the commodity market. For example, for gold and for the three indices, futures prices lead spot prices, and futures prices with longer time to expiration lead futures contracts with shorter time to expiration. Hence the longest contract will keep the price series together in the long run. One implication of this result is that futures prices respond to new information faster than spot prices mostly due to flexibility in short selling and lower transaction costs. Another implication is that, while spot purchases

require more initial capital outlay and may take longer to execute, futures transactions can be implemented immediately by speculators without an interest in the physical commodity per se and with little up-front cash. Moreover, hedgers who are interested in the physical commodity but who do not have much physical storage space would buy futures contracts rather than do spot transactions. Thus, hedgers and speculators react to new information by preferring futures over spot transactions (see Garbade and Silber, 1983). In addition, spot prices react with a lag, because spot transactions cannot be executed as quickly as futures transactions (see Silvapulle and Moosa, 1999). Futures trading can also facilitate in the planning of production and consumption, particularly with a market scheme for inventory levels (see Houthakker, 1992). This indicates that, if futures prices for late deliveries are higher than those for early deliveries, the delay of consumption becomes attractive and changes in futures prices result in changes in spot prices. This way, futures and spot prices converge, which shows the role of the futures market in providing an efficient pricing mechanism.

Furthermore, with reference to the bidirectional causality between the spot and futures prices for aluminum, copper, and silver, it can be argued that potential lead-lag patterns dynamically change as new information arrives in the market. At any time, each may lead the other, as market participants consume and apply information relevant to their positions, whether spot or futures. Support for futures prices' leading spot prices is stronger in terms of empirical evidence and more compelling in the present study, which brings the present study to support the hypothesis of Kawaller et al. (1988). In addition, the findings of this study on the lead-lag relationship of the commodities that were analyzed can be applied to strategy trading in hedging and portfolio investment, because they provide decision-makers with information on the structure and stability of these commodity markets. A lead-lag relationship in the long run implies that traders in these commodity markets (aluminum and copper) have more time to change their positions (long or short) in anticipation of trends in the market or to devise hedging strategies to protect the value of their investments or margins.

Moreover, the findings of this study lay the foundation for new models and theories for asset management, risk management, and trading strategies, as commodity prices regularly play a key role in shaping the dynamics of global economic activity. Fluctuations in commodity prices appear to be key drivers of economic growth, because they affect various economic variables. Thus, learning more about the lead-lag relationship between spot and futures prices, and identifying and investigating the drivers of commodity prices, especially in a time of globalization and digitalization, appear to be an important task that has drawn the attention of financial market researchers and investors.

It can also be noted that lead-lag relationships between spot and futures prices in commodity markets are directly and indirectly linked to various economic drivers. Such drivers include interest rates, exchange rates, convenience yields, money supply, monetary policy uncertainty, stock prices, global and monetary liquidity conditions, asset prices spillovers, and capital flows.² These studies support the notion that commodity prices could act as early indicators of the future direction and trends of the economy, as they are continually auctioned in standardized markets with efficient information (Cody and Mills, 1991; Marquis and Cunningham, 1990). Therefore, the findings given in this article,

particularly the lead–lag relationships between spot and futures prices, can give insight into the future paths of the economy and can relate to new economic models and theories for financial market strategies. Such mathematical trading models must still be developed and should include the results through the present study. It is also true that the futures of financial markets can influence the study results, particularly the lead–lag relationships between spot and futures prices. It is evident, for instance, that rising commodity prices are usually attributed to an expansionary monetary policy and consistently low interest rates (see Apergis et al., 2020; Frankel, 2006). It is therefore increasingly important to understand the extent to which monetary policy affects commodity price movements.³

The present study can be augmented through future research by looking at potential variables such as exchange rate, interest rate, inflation rate, growth rate, and monetary policy while determining the linkage between spot and futures prices in commodity markets. Why there is a difference in market efficiency in and between different commodity markets is unclear and might be the focus of further investigation. Finally, the prevalence of asymmetries in time series data due to various financial market policies warrant the use of non-linear empirical methods such as non-linear ARDL, developed by Shin et al. (2014), rather than linear approaches.

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