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Copper futures market of India: dissections of price discovery, volatility and hedging

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Laxmidhar Samal
Department of Commerce, Baba Bhairabananda Autonomous Mahavidyalaya, Jajpur, India, and
Satyajit Singh
Emirates NBD Bank PJSC, Dubai, United Arab Emirates

Abstract

Purpose – This piece of research aims to investigate the influential direction of price dissemination, hedging efficacy and shock transmission of the copper futures market in India.

Design/methodology/approach – The study selects the high-frequency closing prices of cash and futures series data from the Multi-Commodity Exchange of India for seven years. To examine the objectives of the study, cointegration, the error correction model, EGARCH and the hedge ratio are employed.

Findings – In contrast to the short run, in the long run, information flows bidirectionally for price discovery. The futures market of copper indicates strong endogeneity in the short run. The study observes a lack of hedging efficacy in the full and sub-sample period. A shed of evidence is found in support of bidirectional shock transmission. The scalping index shows a large number of speculative activities in the copper futures market.

Practical implications – The study findings will help traders and portfolio managers in designing trading strategies and portfolio selection. The study answers the question for the hedgers regarding the number of futures positions they need to hold to avoid their cash exposure. Finally, the regulating agency and government will be able to frame policies for further developing the copper market.

Originality/value – The paper evaluates the most significant aspects of the copper futures market, viz. price dissemination, volatility and hedging efficacy. To the best of the authors' knowledge, studies on efficacy and shock transmission in the context of the copper futures market in India are rare. Further, the study also contributes by exploring the price dissemination process and hedging of the metal futures market.

Keywords Price discovery, Hedging, Copper, Unbiasedness, Volatility

Paper type Research article

Introduction

Commodities, especially base metals, play an important role in shaping the economy of the country. Base metals are used as key inputs for producing capital goods and are hence regarded as the backbone of industrial production. Copper is one of the other metals which has been used by human beings since the early stages of civilisation. Because of its inherent qualities like ductility, malleability, being a good conductor of heat and electricity, antimicrobial, etc., it is one of the most widely used metals in the world. The Government of India lifted restrictions on commodity futures trading in 2003, and after that, there has been robust growth in commodity futures trading in India. After lifting restrictions on commodity futures trading, this segment has been gaining momentum. Stakeholders like producers, consumers, importers, exporters, etc. participate in hedging cash market exposure, price discovery, price risk management, etc.

JEL Classification — C32, C50, G15

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Figure 1 depicts that over the last decade, the futures market witnessed steady growth in its average daily turnover. Development of domestic benchmarks, allowing fund houses to participate in the commodity segment and permitting the trading of commodity index futures, are the main causes of such growth in average daily turnover. In the financial year 2019–2020, the average daily turnover registered about 23% growth over the previous year. Similarly, the average daily turnover of base metal futures traded on the MCX platform also registered strong momentum over 15 years. Since 2014–2015, the average daily turnover of the metal futures segment has been rising steadily.

The commodity futures market has the inherent quality to discover future spot prices and provide hedging efficacy to the hedgers. The futures market attracts more participants because of its functions of price discovery and hedging and provides justifications for its trading (Garbade & Sibler, 1998). Besides hedgers, speculators and arbitrageurs also participate, intending to reap profit by predicting the market movements (Easwaran & Ramasundaram, 2008). Any movement in prices gives rise to two things: first, the risk and second, the profit potential. The hedgers pass the risk by holding a long-term view of the market, whereas speculators accept the risk with a desire to reap profit by holding a short-term view of the market. Arbitrages help to correct the price differentials, if any, between the markets. Therefore, the futures price reflects the views and expectations of all the participants (Park & Lim, 2018). Through price discovery and price risk management, the futures market helps participants to manage their future sales or purchases and to manage their stock position.

The producers, consumers, exporters, importers and others participate in the commodity futures market with diverse national and international information and with different views and needs, which affect the futures prices of the commodity. At the time of arrival of new information, the futures markets act quickly to discount it so as to reflect the future spot price (Gupta & Singh, 2006). According to Dey and Maitra (2012), the basic objective of price discovery is to identify the true value of the underlying commodity. Chan (1992) opined that the futures market is popular because of its function of risk management and forecasting power. According to Biswal (2008), at the time of the arrival of new information, both cash and futures markets act simultaneously, and an efficient market does not have a lead-lag relationship. Microstructure effect, short sale, transaction cost, etc. affect the lead-lag relationship.

The study is an attempt to answer the following questions: Is the copper futures market successful in performing the function of price discovery? Is the copper futures market an unbiased predictor of its future spot price? Does the copper futures market have hedging efficiency? How many futures positions do the hedgers need to hold in order to mitigate their spot exposure? Does there exist volatility spillover between the markets of copper? The next section of the paper discusses the existing literature. The third part contains the methodology of the study. The fourth section deals with data analysis and results discussion, and in the last part, the study provides the conclusion.

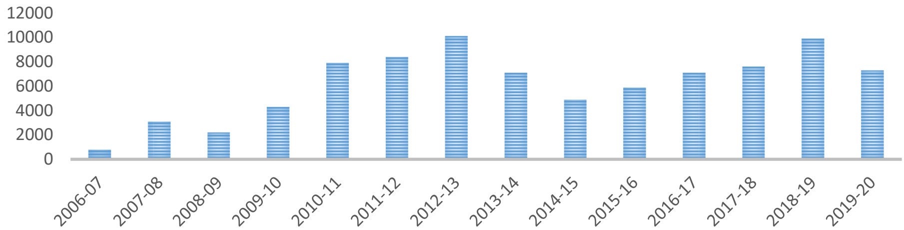

Figure 1. ADT in base metal futures (Rs. crore). Source: Commodity insight year book 2021, MCX, India

Review of literature

Globally, extensive studies have been made concerning price discovery, hedging and volatility characteristics of the commodity futures market. When the information content of the futures price reflects the fundamental value of the underlying commodity, it is known as the price discovery process of futures. According to Dey and Maitra (2012), price discovery helps the market participants identify the intrinsic value of the commodity. Bakaert and Harvey (1997) found evidence regarding the poor information content of the futures market of emerging countries. In a similar study, Kumar and Pandey (2011) reveal that the Indian commodity futures market is not successful in price discovery as compared to developed nations.

Dimpfl, Flad, and Jung (2017) considered eight commodities and found that in the long run, the spot has a major role in determining the prices. Shrestha and Thiyagarajan (2020) considered agricultural commodities and used information share and component share measures to study the price discovery and concluded that, unlike the other selected commodities, the cocoa cash market leads the price discovery. Manogna and Mishra (2020) used an error correction model and selected nine commodities to study the price discovery mechanism. Their study supports the role of futures in price discovery, whereas in the case of the other three commodities, spot leads the price discovery. Karabiyik, Narayan, and Phan (2018) supported Manogna and Mishra (2020) and chose Islamic stocks from 19 markets and concluded that the spot market dominates the price discovery process. Ahumada and Cornejo (2016) considered the soybean market and used a multivariate framework to test the price discovery and concluded that the futures market of soybean can predict its future cash prices.

Ates and Wang (2005) evaluated the information transmission process between the electronic and open outcry systems and supported the role of both the market for price discovery. Samal and Das's (2023a, b) findings are in line with Ates and Wang (2005), they select the aluminium cash and futures series and observe that both markets of aluminium influence each other for price discovery. Liu and An (2011) chose copper and soybeans traded in the USA and Chinese futures market and evaluated the price discovery by employing the M-GARCH model and found that the futures market plays a dominant role in price discovery. Figuerola-Ferretti and Gonzalo (2010) considered nonferrous metals traded at the London Metal Exchange and supported the information-dominant role of the selected futures prices. By employing cointegration and VECM, Nair (2021) studied the metal futures market and found that the futures take the leading role in price discovery. This piece of research supported Figuerola-Ferretti and Gonzalo (2010).

In a similar approach, Fasses *et al.* (2020) choose bitcoin futures and supports the leading role of futures in price discovery. In contrast to Samal and Das (2023a, b), Mishra and Kumar (2022) studied the role of commodity futures in price discovery by using component share and information share measures and concluded that commodity indices play an important role in price discovery. Xu (2018) considered the corn futures traded at the Chicago Board of Trade and found evidence in favour of the futures market playing the leading role in price discovery. Martin, Christian, and Waldemar (2019) studied the price formation process of the USA and Brazilian coffee markets and supported the leading behaviour of futures in price discovery. Clark used the contracts traded at the London Metal Exchange and supported the existence of short- and long-run causality between the markets. Pani, Gherghina, Mata, Ferro, and Mata (2022) find no lead-lag relationship between the cash and futures of selected base metals. In contrast to Pani *et al.* (2022) supported the lead-lag relationship of the energy futures of India. In another paper, Samal and Das (2022) evaluated the nickel futures market and found unidirectional causality between the cash and futures market of nickel in the long run. Yang and Lepone (2025) examined the crude oil derivatives market of China and concluded that speculation has a significant contribution to the price discovery of the futures market of the commodity as compared to the options market. Lee and Vedenov (2025) studied a joint hedging strategy for price risk (input) and exchange rate risk (output) of the US soybean export to Europe. It is revealed that joint hedging increases the hedging effectiveness. Further, it is found that the choice of a single or joint hedging strategy depends upon the interconnectedness between soybean and FX rates. Jain and Maitra (2025) explored the price crash risk of commodities and concluded that the forces of speculation and hedging cause the exacerbation of crash risk, whereas the basis decreases the crash risk of selected commodities. Samal (2025) examined the lead futures market and concluded that the cash market does not contribute to the price discovery of the futures of the selected commodity over the study period. Bermpei and Triantafyllou (2025) studied the marginal convenience yield in selected agricultural commodities and concluded that it is negative on average during the commodity financialisation period.

Volatility affects the futures market return and impacts price discovery. When both markets are co-integrated, there is the possibility of a spillover effect. Anderson (1985) considered nine commodities and found that the variance of futures price change is not constant and does not follow a regular pattern. Locke and Sarkar (1996) studied the volatility and liquidity characteristics of the futures market and found that for inactive contracts, the liquidity provisions become more profitable for price-sensitive customers. Zhong, Darrat, and Otero (2004) examined the volatility pattern of Mexico index futures and supported that futures volatility causes instability in the cash market.

Floros and Vougas (2006) examined Samuelson's hypothesis by considering Greek stock index futures and found evidence in support of Samuelson's hypothesis. In contrast, Gupta and Rajib (2012) found no evidence in support of Samuelson's hypothesis. They considered eight commodities from the Multi-Commodity Exchange of India. Chang, MCAleer, and Tansuchat (2012) examined the long-memory volatility of the futures market by considering the 16 agricultural commodities and supported the long-memory volatility of the futures market. Manera, Nicoloni, and Vignati (2013) studied the volatility dynamics of the commodity derivative market by considering the energy and non-energy commodities and concluded that speculation has a significant impact on the volatility of returns. Sendhi, Kar, Mathur, and Jha (2013) considered the food grain futures contract of India, evaluated the volatility characteristics and concluded that derivative trading causes persistent volatility in the cash market.

Gupta and Varma (2016) chose rubber futures contracts available in the NMC Exchange of India for nine years and found evidence of futures causing volatility in the cash market. Malhotra and Sharma (2016) considered oil and oilseed futures and studied the volatility transmission between the markets. Their study observes the bidirectional transmission of volatility between the selected commodities. Kang, McIver, and Woon (2017) employed the DECO-GARCH model to study the volatility transmission of six selected commodities and found that bidirectional return and volatility spillover among the selected commodities. Mukherjee and Goswami (2017) evaluated the volatility of the Indian commodity futures market and found that the volatility is sensitive towards their lagged values. Samal (2024a, b) extended the work of Mukherjee and Goswami (2017) and concluded that there prevails a spillover of shock between the markets of energy commodities. Mo, Gupta, Li, and Singh (2018) employed the GARCH-MIDS model and made a comparative study between the Indian and Chinese futures markets and concluded that both national and global economic parameters impact the volatility of selected commodities.

Hu, Zhang, Ji, and Wei (2020) examined the relationship between the macro factors and the volatility of commodity futures and found that there exists information spillover between the macro factors and the selected futures market. Zeng, Abedin, Ahmed, and Lucey (2025) support the spillover between climate policy uncertainty and the grain commodity market. In a similar study, Ma, Zhou, and Li (2024) found that global warming has greater predictability of the return variability as compared to transaction risk. By extending Hu *et al.* (2020), Sreenu, Rao, and Kishan (2021) supported that the macro variables have a positive impact on the variance of selected futures. Truong, Friday, and Nguyen (2022) studied the impact of index futures trading on the volatility of the cash market and found a positive relationship. Liu, Li, Putnam, and Yu (2025) studied the speculation and volatility in the energy futures market and found that, in the case of crude oil, due to the network effect, speculation impacts the price volatility. On the other hand, the direct effect of speculation dominates the natural gas market.

There is a large number of studies worldwide covering the informational efficiency, volatility and hedging efficacy of commodity futures. But the number of research studies is countable in terms of developing nations as compared to developed countries. Particularly concerning India, studies are very limited in covering the metal futures segment. Studies consider that monthly data does not portray the information correctly, and studies that used data before 2013 were not able to inculcate the growth momentum of the metal futures market. Moreover, the commodity transaction tax was imposed in the financial year 2013–2014; therefore, these studies do not capture this effect. Further research papers checked that only the price discovery function of metal futures would not provide information on volatility, hedging and unbiasedness (Samal & Das, 2023a, b). In light of the above fact, this study is an attempt to answer the following questions: Is the copper futures market successful in performing the function of price discovery? Is the copper futures market an unbiased predictor of its future spot price? Does the copper futures market have hedging efficiency? How many futures positions do the hedgers need to hold in order to mitigate their spot exposure? Does there exist a bidirectional volatility spillover between the markets of copper?

Data and empirical methods

Data

Table 1 presents the spot and the futures series of copper used in the study. The study period ranges from April 2013 to March 2020. Cash price refers to the cash price (₹/Kg.) of copper that prevails in Mumbai, India, while the futures price of copper indicates the closing price of near-month futures contracts (5 MT contract) traded at MCX, India. The study chooses the cash and futures prices of copper by considering that India ranks 6th and 9th in terms of global production and consumption of copper. The producers and consumers are exposed to the price risk of the physical market. Secondly, the commodity is chosen by considering the market liquidity, open interest position and availability of data. The study does not consider the data of the financial year 2020–2021 to avoid the COVID-19 impact.

Empirical methods

Unit root test

Descriptive statistical methods are used to analyse the basic characteristics of the price series of copper. Initially, the stationarity of the variables is examined by using the ADF (Dickey & Fuller, 1979) and the PP test (Philips & Perron, 1988). The random walk-based regression equation with a drift is specified as:

$$\Delta y_t = \varphi + \partial y_{t-1} + \sum \theta \Delta y_{t-j} + u_t \tag{1}$$

The null hypothesis is stated as H_0: $\partial = 0$, against the alternative of H_1: $\partial < 0$.

Table 1. Data sample

Base metal	Market	Platform	Period	Size
Copper	Spot	Mumbai, India	7 years	5 MT
	Futures	MCX, India	7 years	5 MT

Source(s): Authors' calculation

Co-integration test

The long-run relationship is examined by using Johansen's cointegration test (Johansen, 1995), which can be specified as:

$$H_1(r)\colon \Pi_{y_t-1} + Bx_t = \alpha(\beta' y_{t-1} + P_0) + \alpha_{\perp}\gamma_0 \tag{2}$$

By using trace (λ_{trace}) and maximum eigenvalue (λ_{max}) tests, the null hypothesis of no cointegrating relationship is verified. If pieces of evidence for the existence of the cointegrating relationship between the markets are found, then the vector error correction model (VECM) will be used to evaluate the direction of price discovery.

Vector error correction model (VECM). The two-variable restricted form of the VAR (VECM) model can be specified as:

$$\Delta \ln S_t = a + \sum_{i=1}^{k-1} \beta_i \Delta \ln S_{t-i} + \sum_{j=1}^{k-1} \phi_J \Delta \ln f_{t-J} + \lambda_1 ECT_{t-1} + u_{1t} \tag{3}$$

$$\Delta \ln f_t = a + \sum_{i=1}^{k-1} \beta_i \Delta \ln S_{t-i} + \sum_{j=1}^{k-1} \phi_J \Delta \ln f_{t-J} + \lambda_2 ECT_{t-1} + u_{2t} \tag{4}$$

The adjustment parameter is indicated through λ_i. Similarly, the error correction term is indicated by ECT_{t-1}. It is the lagged values of the residuals obtained from the co-integrating regression of the dependent variable on regressors. Similarly, u_{it} refers to the residuals of the model. The lag length is selected according to the Akaike information criterion.

Minimum variance hedge ratio

To measure the hedge ratio, the approach of this study followed that of Samal and Das (2023a, b) and Swain and Samal (2017). After calculating the return of the series, i.e. $\Delta S = S_t – S$ and $\Delta F = F_t – F$, the minimum variance hedge ratio is evaluated. When the hedger holds a long cash and short futures position, the portfolio value will be $1S_0 + h \times F_{(0,\ T)}$. The results of the portfolio on the date of offset can be written as:

$$[1(S_t - S_0) - \{h \times \{F_{(t,T)} - F_{(0,T)}\}\}] \tag{5}$$

Similarly, the variance of the portfolio will be as follows:

$$1^2 \operatorname{Var} \Delta S + h^2 \operatorname{Var} \Delta F - 2(1)(h) \operatorname{Cov}(\Delta S, \Delta F) = \operatorname{Var} \Delta S + h^2 \operatorname{Var} \Delta F - 2h \operatorname{Cov}(\Delta S, \Delta F) \tag{6}$$

By considering Eq. (6), the variance hedge ratio (h) can be stated as

$$h = \rho(\sigma \Delta S)/(\sigma \Delta F) \tag{7}$$

Where the scaling factor (ρ) is multiplied by the ratio of $\sigma \Delta S$ to $\sigma\ \Delta F$.

EGARCH (1, 1) model

Volatility is an important dimension of time series analysis. Before applying the GARCH model, the existence of the ARCH effect is tested to check the volatility clustering. The GARCH model neutralises both conditional variances of informational, but both have a different impact on volatility spillover (Bollerslev, 1986). Therefore, to avoid this, the present piece of research considers the bivariate EGARCH (1, 1) model for the estimation of volatility spillover. The bivariate EGARCH (1, 1) model is specified as follows:

$$P_t = \alpha_0 + \sum_{i=1}^{r} \alpha_i P_{t-1} \tag{8}$$

Where, $\varepsilon = \varepsilon_{f,\frac{tt}{\varepsilon_s,\varphi_{t-1}}} \mathbb{N}(0, \beta_t)_{\beta_t} = [\omega_{ij}, \varsigma_i, t, \varsigma_j, t]$

$$\log\left(\delta_t^2\right) = E\left\{\alpha_0 + \sum_{t=1}^{q} \alpha_{i\,g(z_{t-i})}\right\} + \sum_{i=t}^{p} \beta_i \log \varsigma_{t-1}^2 \tag{9}$$

$$\mathrm{G}(\mathrm{Z}_t) = \theta \mathrm{z}_t + [|\mathrm{z}_t| - E|\mathrm{z}_t|] \tag{10}$$

$$\mathrm{Ln}\left(\varsigma_t^2\right) = \alpha_1 \left(\frac{\varepsilon_{t-1}}{\varsigma_{t-1}^{0.5}}\right) + \lambda_1 \left|\left(\frac{\varepsilon_{t-1}}{\varsigma_t^{0.5}}\right)\right| + \beta 1\mathrm{n}\left(\varsigma_{t-1}^2\right) \tag{11}$$

$$\mathrm{Ln}\left(\varsigma_{f,t}^2\right) = \varsigma_f + \gamma_f \left[\frac{\varepsilon_{t-1}}{\zeta_{t-1}} - \sqrt{2/\pi}\right] + \rho_f \ln \frac{\varepsilon_{t-1}}{\zeta_{t-1}} + \alpha_f \ln\left(\varsigma_{2,t-1}^2\right) + \vartheta_f \ln\left(\varepsilon_{s,t-1}^2\right) \tag{12}$$

$$\mathrm{Ln}\left(\varsigma_{f,t}^2\right) = \varsigma_s + \gamma_s \left[\frac{\varepsilon_{t-1}}{\zeta_{t-1}} - \sqrt{2/\pi}\right] + \rho_f \ln \frac{\varepsilon_{t-1}}{\zeta_{t-1}} + \alpha_s \ln\left(\varsigma_{2,t-1}^2\right) + \vartheta_s \ln\left(\varepsilon_{f,t-1}^2\right) \tag{13}$$

Equation (1) indicates the "conditional mean equation on the autoregressive process of order r". The z_t refers to the standardised residual t−1; ς_t^2 and φ_{t-1} indicates informational bias at time t−1. The conditional variance is indicated by ς_t^2; a stochastic error by ε_t, which is assumed to be normally distributed with zero mean and conditional variance. The sign effect and the size effect are reflected as a shock on volatility, which is presented in Equation (10). Equation (11) captures the leverage effect. If $\frac{\varepsilon_{t-1}}{\zeta_{t-1}^{0.5}}$ is negative, the effect of shock on the conditional variance is $(-\alpha_1 + \lambda_1)$, and otherwise, the effect of shock on the log of variance is $\alpha_1 + \lambda_1$. The bivariate EGARCH (1, 1) model is concluded by Equation (13).

Data analysis and results

Figures 2 and 3 depict the trend of cash and futures prices of copper. The selected price series shows a similar trend over the period chosen for the study. From 2013 to the end of 2016,

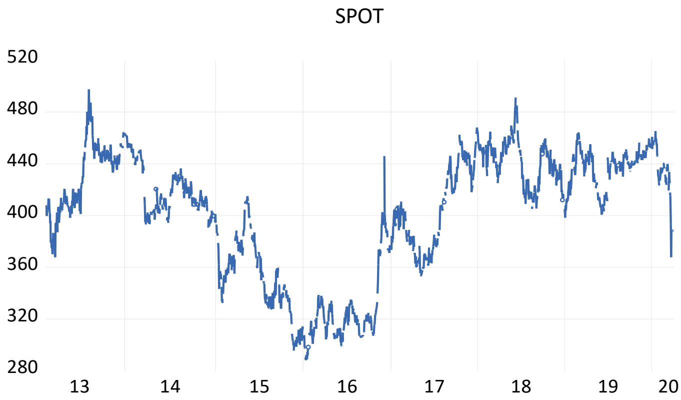

Figure 2. Price series of copper cash. Source: Authors' calculation

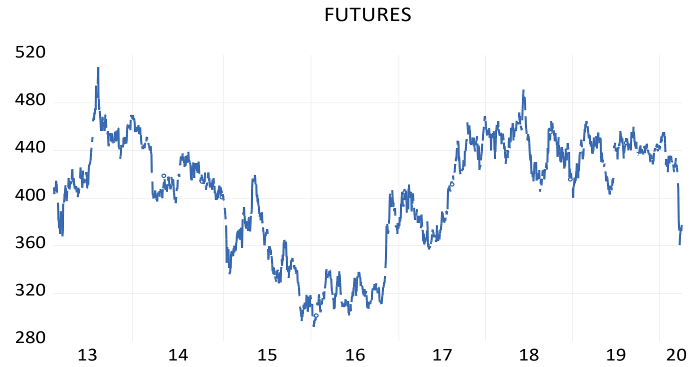

Figure 3. Price series of copper futures. Source: Authors' calculation

there was a downwards trend in the prices of copper. The price of copper was about Rs 400 per kg at the beginning of the financial year 2013 and then rallied to almost Rs 500 per kg. Since the start of 2014, it has started decreasing and touched about Rs 250 per kg by the end of 2016. At the end of the financial year, 2019, prices of both markets consolidated to about ₹360 per kg.

The results listed in Table 2 present the basic characteristics of the selected markets of copper. The maximum and minimum cash prices of copper are Rs. 497.55 and Rs. 288.25, respectively, over the study period, whereas the maximum and minimum futures prices are Rs. 509.95 and Rs. 291.90, respectively. The mean and median values of futures prices are higher than those of cash. There exists the same level of fluctuation in the copper cash and futures market. The price series is negatively skewed and platykurtic.

First, the price series are transposed into their logarithm form, then the ADF and PP unit root tests are used to check the stationarity of the data. The results of the unit root test are listed in Table 3, indicating that the price series are found to be nonstationary at the level but become stationary at I (1). Both the test models show similar results at three specifications, viz. intercept, intercept and trend and none. Hence, the study rejects the null of the presence of a unit root at I (1) in both the price series.

The order of integration between the price series is the same; hence, to check the long-run relationship between the spot and futures, we are now motivated to perform a cointegration

Table 2. Descriptive statistics

Descriptive stat.	Copper Cash	Future
Mean	402.12	404.36
Median	412.75	415.47
Maximum	497.55	509.95
Minimum	288.25	291.90
Std. dev.	47.60	47.44
Skewness	−0.67	−0.66
Kurtosis	2.34	2.33
Jarque–Bera	173.27	167.90
Probability	0.00	0.00
Sum	744732.0	748868.7
Sum Sq. dev.	4,194,716	4,165,468
Observations	1852	1852

Source(s): Authors' calculation

Table 3. Unit root test for cash and future prices of copper

Test	Series	Spec.	*t*- stat and *p*-value	Test	Series	Spec.	*t*- stat and *p*-value
ADF	lncash	C	−2.015 [0.280]	*PP*	lncash	C	−2.048 [0.266]
		C and T	−2.051 [0.572]			C and T	−2.091 [0.549]
		None	−0.125 [0.641]			None	−0.139 [0.635]
	lnfutures	C	−1.996 [0.289]		lnfutures	C	−2.065 [0.259]
		C and T	−2.001 [0.599]			C and T	−2.081 [0.555]
		None	−0.196 [0.616]			None	−0.194 [0.616]
	Δ lncash (First differenced)	C	−47.979 [0.000]*		Δ lncash (First differenced)	C	−47.986 [0.000]*
		C and T	−47.966 [0.000]*			C and T	−47.973 [0.000]*
		None	−47.992 [0.000]*			None	−47.999 [0.000]*
	Δ lnfutures (First differenced)	C	−43.713 [0.000]*		Δ lnfutures (First differenced)	C	−43.718 [0.000]*
		C and T	−43.701 [0.000]*			C and T	−43.708 [0.000]*
		None	−43.724 [0.000]*			None	−43.729 [0.000]*

Note(s): *Indicates that the values are significant at a 1 per cent statistical level
Values within [ ] refers to *p*-values
Source(s): Authors' calculation

test. The results tabulated in Table 4 indicate that there exists one cointegrating vector between the cash and futures market of copper. By considering the trace (λ_{trace}) and maximum eigenvalue test (λ_{max}), the study rejects the null of no cointegrating relationship (Samal, 2024a, b). The study supports the existence of a long-run relationship between the markets of copper. Now it is essential to employ the ECM model to check the direction (short run and long run) of price discovery between the markets. The results of the VEC model tabulated in Table 5 show that the error correction terms of both the markets are significant, which states that when

Table 4. Results of Johansen's co-integration

Metal	Test	H_0	Test statistic	Critical value (0.05)	"*p*"-value
Copper	Trace	$R = 0$	292.917	15.494	0.000*
		$R = 1$	3.617	3.841	0.057
	Maximum eigenvalue	$R = 0$	289.300	14.264	0.000*
		$R = 1$	3.617	3.841	0.057

Note(s): "*R*" refers to the number of cointegrating vectors under the null hypothesis
*Indicates that the null hypothesis is rejected at a 1 per cent statistical level
Source(s): Authors' calculation

Table 5. Results of error correction model

Copper $\Delta\ln S_t$			$\Delta\ln F_t$		
$\Delta\ln S_{t-1}$	$\Delta\ln F_{t-1}$	€	$\Delta\ln S_{t-1}$	$\Delta\ln F_{t-1}$	€
0.192**	0.314**	0.335**	−0.029	0.024	−0.060**
[−7.707]	[10.373]	[13.234]	[−1.126]	[0.768]	[−2.306]

Note(s): € = Error correction term; [ ] *t*-statistics and ** Significant at 5%
Source(s): Authors' calculation

there is disequilibrium in the market, both the cash and futures markets of copper increase and decrease simultaneously to reach the equilibrium. Further, it implies that the information flows bidirectionally, i.e. from the futures market of copper to its cash market and vice versa.

To check the short-run information flow for price discovery between the cash and futures market of copper, the study uses two ways of causality checks, i.e. the block exogeneity Wald test and the Granger causality test. The results of causality checks presented in Tables 6 and 7 show that there exists unidirectional causality between the price series of copper. Both tests present the same results. In the short run, there exists an influential direction from futures to cash for price dissemination. But there is no flow of information from the cash to the futures market of copper for dissemination.

It is evident from Table 8 that at the initial period, a hundred per cent of "forecasted error variance" in futures is explained by the variable itself. The first-day futures market is explained by itself, and the cash does not influence it. For all other periods, also more than 99 per cent of the "forecasted error variance" in futures is explained by itself. Hence, the futures market of copper indicates strong endogeneity in the short run. During the first period, almost 30 per cent of the forecasted error variance in cash is explained by the futures market of copper. The influence of the futures market of copper increases gradually on cash. For the third day, almost 50 per cent of the "forecasted error variance" in cash is explained by the futures market of copper. Similarly, the exogeneity of futures increases for the fourth day, and approximately 72

Table 6. VECM Granger causality/block exogeneity Wald test

Commodity	H_0	Chi-square	Prob.	Relation
Copper	Cash does not cause futures	1.267	0.260	Unidirectional
	Future does not cause cash	107.609	0.000*	

Note(s): *indicates that the null hypothesis is rejected at a 1 per cent statistical level
Source(s): Authors' calculation

Table 7. Granger causality results

Commodity	H_0	*F*- stat.	Prob.	Relation
Copper	Cash does not Granger cause future	4.654	0.080	Unidirectional
	Future does not Granger cause cash	301.756	0.000*	

Note(s): *Indicates that the null hypothesis is rejected at a 1 per cent statistical level
Source(s): Authors' calculation

Table 8. Results of variance decomposition

Cash series of copper			Futures series of copper		
Period	lncash	lnfutures	Period	lncash	lnfutures
1	70.002	29.998	1	0.000	100.000
2	50.077	49.923	2	0.071	99.929
3	36.661	63.339	3	0.152	99.847
4	28.207	71.793	4	0.221	99.779

Source(s): Authors' calculation

per cent of the "forecasted error variance" in cash is explained by the futures market. Unlike the futures market, the cash market of copper indicates strong exogeneity in the short run.

Now it is required to test whether the copper futures market is an unbiased estimator of its future cash price or not. By following Fama and French (1987), the return of spot is regressed with the basis of copper. Then the joint hypothesis ($\alpha = 0$, $\beta = 1$) is tested to determine the (Fama & French, 1987) unbiasedness of the copper futures market. The regression results presented in Table 9 reflect that the β value is positive and significant. Therefore, it indicates that the futures price of copper has the power to forecast its future spot price. However, the basis explains only 15 per cent of the copper cash market return. The joint hypothesis ($\alpha = 0$, $\beta = 1$) is rejected at a significant level, which shows that the futures price of copper is not an unbiased estimator of its future cash price.

The study rejects the unbiasedness hypothesis of the copper futures market; however, the copper futures market discovers the prices of its corresponding cash. Is the market helpful for the hedgers to manage their spot market risk? How many futures positions should the traders hold to mitigate cash segment risk? This is answered through the hedge ratio. If p between Δs and Δf will be one, and the σ of Δswill is equal to the σ of Δf of copper, then the h will mean the futures price mirrors the cash price perfectly (Das, 2013). It is evident from Table 10 that for the 2013–2014 and 2014–2015 financial years, the hedge ratio is negative. Even though the ratio between σ of Δs and σ of Δf is 1.08 and 1.00 for 2013–2014 and 2014–2015, respectively, the scaling factor is negative; therefore, the hedge ratio shows a very dismal picture. The minimum variance hedge ratio has increased gradually, and by the end of 2016–2017, it is almost one, which indicates the futures price perfectly mirrors the cash price of copper. The

Table 9. Regression results

Dependent: spot return Copper	Coefficient	Std. err.	t	Sig.
Constant (α)	0.332	0.130	2.543	0.011
Basis (β)	0.153	0.023	6.562	0.000
Results of coefficient restriction				
Null (H_0)	Test stat.		Sig.	
$\beta = 1$	836.47		0.000*	
$\alpha = 0, \beta = 1$	36.40		0.000*	

Source(s): Authors' calculation

Table 10. Minimum variance hedge ratio

Year	ρ	σ Δ S	σ Δ F	σ Δ S/σ Δ F	Hedge ratio
2013–2014	−0.05	5.38	4.97	1.08	−0.05
2014–2015	−0.03	4.49	4.47	1.00	−0.03
2015–2016	0.29	4.87	4.41	1.10	0.32
2016–2017	0.78	6.07	4.47	1.36	1.06
2017–2018	0.92	4.76	4.56	1.04	0.96
2018–2019	0.87	5.3	5.14	1.03	0.90
2019–2020	0.44	5.3	4.39	1.20	0.53
2013–2020	0.45	5.27	4.37	1.21	0.54

Note(s): *Indicates that the null hypothesis is rejected at a 1 per cent statistical level
Source(s): Authors' calculation

association between cash and futures is highest in 2017–2018, and the hedge ratio is found to be 0.96. After 2016–2017, the hedge ratio decreases gradually and by the end of 2019–2020, it is found to be 0.53. The full sample period indicates that 0.53 units of futures positions are required to hedge 1 unit of cash market exposure of copper. The full sample period and except for the financial year 2016–2017, all sub-sample period indicates a lack of hedging effectiveness in the copper futures market.

When there is a long-run relationship between the two segments of copper, i.e. cash and future, there is the possibility of volatility spillover of price fluctuations between the markets. The standard GARCH model treats both good and bad news symmetrically; hence, informational biases (market advances and downfalls) have a symmetric effect on asset volatility. Therefore, this piece of research considered the EGARCH (1, 1) model for the estimation of volatility, which treats asymmetrically the informational biases, i.e. market advances and downfalls. It is evident from Table 11 that the volatility spillover exists from cash to futures and vice versa. The α_i refers to the informational bias term, which indicates that negative shocks impact the volatility spillover from one market to another. It is found that there exists an informational bias in the cash-to-futures segment and vice versa.

Figures 4 and 5 present the volume-open interest graph and the scalping index of the copper futures market, respectively. Table 12 exhibits the yearly average of the scalping index.

Table 11. Results of volatility spillover

Coefficient	Copper (futures to cash)	Copper (cash to futures)
ς_i	0.617 * (41.687)	1.180 * (60.254)
γ_i	−0.846* (−13.275)	−0.409 * (−4.852)
ρ_i	0.359 * (17.603)	0.101 * (7.058)
α_i	−0.057 * (−3.244)	−0.018* (−2.861)
ϑ_i	0.935 * (144.432)	0.962 * (109.650)

Source(s): Authors' calculation

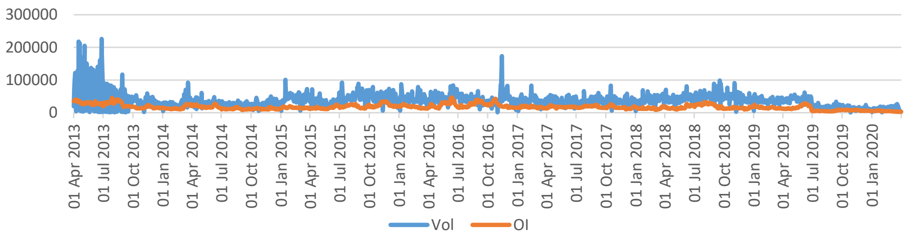

Figure 4. Volume and open interest. Source: Authors' calculation

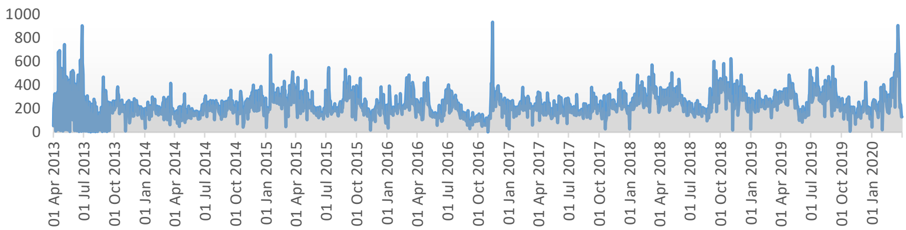

Figure 5. Scalping index. Source: Authors' calculation

Table 12. Scalping index (yearly average)

Year	Copper (%)
2013–2014	233.58
2014–2015	224.44
2015–2016	233.64
2016–2017	200.58
2017–2018	231.88
2018–2019	270.01
2019–2020	271.97
2013–2014 – 2019–2020	237.86

Source(s): Authors' calculation

The scalping index is a proxy of the ratio of volume to open interest of a futures contract. It exhibits the speculation level in the market (Samal, 2025). A higher scalping index indicates a higher level of noise in commodity futures contracts (Algieri & Leccadito, 2018). According to Roswell and Purcell (1992), "scalpers trade price ticks, holding a position for a matter of moments, anticipating the last price change will be followed by an opposite price move". The average scalping index for the sub-sample as well as the full sample years is found to be more than 200 per cent over the period chosen for the study. The index was found to be lowest in the year 2016–2017 and highest in 2019–2020. The average scalping index for the full sample year is almost 238 per cent of the selected commodity over the chosen study horizon. Due to the scalper's activity, the change in the volume of futures contracts over their open interest is considered speculation (Manera *et al.*, 2013). According to Algieri and Leccadito (2018), "scalping activities increase noise more than other long-run speculative activities". The result of the scalping index exhibits the speculative activities in the copper futures contract.

Conclusion

Copper is one of the other metals that have been used by human beings since the early stages of civilisation. Because of its inherent qualities like ductility, malleability, being a good conductor of electricity and antimicrobial, it is the most widely used in the world. The study supports the long-run relationship between the cash and futures segment of copper. In the short run, there exists an influential direction from futures to cash for price discovery, which is in contrast with Liu and An (2011). According to the results of variance decomposition, the futures market of copper indicates strong endogeneity in the short run, whereas the cash market of copper indicates strong exogeneity. It is observed that there exists an informational bias in the cash-to-futures segment and vice versa. The present study rejects the unbiasedness hypothesis of the copper futures market (Samal, 2024a, b). The full sample period and except for the financial year 2016–2017, all sub-sample period indicates a lack of hedging effectiveness of copper futures traded at MCX, India. Copper markets indicate a bidirectional spillover of volatility. Further, the study found a large number of speculative activities in the copper futures market.

According to Rajib (2021), the physical base metal market of India is oligopolistic, and a few large sellers are in an advantageous position to influence the delivery of the commodity; hence, there is low hedging efficiency and persisting backwardation in the metal futures market. Importantly, a large segment of copper is tiny in size and widely dispersed across the country (Samal and Das, 2023a, b). Moreover, these tiny segments are exposed to technical constraints and margin inadequacy (Jacob, 2019). Further, the oligopolistic nature of the metal futures market creates inefficiency (Samal, 2024a, b). The conclusion of the study can be used to understand the influential direction of price discovery and the unbiasedness of the copper futures market. The findings of the study will help traders design trading strategies.

The portfolio managers can use the volatility information for their portfolio adjustment. The study answers the hedgers' question about the number of futures positions they need to hold to avoid their cash exposure. The producers and consumers of copper will be able to decide the number of copper futures contracts they ought to hold in order to manage spot market risk. Finally, the regulating agency, academicians and government will be able to frame policies for further developing the copper market. The present study considers only one metal from the Indian commodity exchange, which can be extended by future research. The future research will explore the dynamics between the precious and base metals in an international context. Further, the interconnectedness between the metal futures traded at the London Metal Exchange and the Indian Commodity Exchanges is left for future research.

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Corresponding author
Laxmidhar Samal can be contacted at: laxmidharsamal.ckl@gmail.com