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From stability to swings: Metal and bullion price volatility in India's post-covid commodity market

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Abstract
This study explores the post-COVID-19 volatility and interlinkages among precious metals (Gold, Silver) and base metals (Aluminium, Copper, Nickel, Zinc, Lead) in India using daily spot price data from December 2020 to December 2024. Employing ADF and PP tests, Johansen co-integration, Granger causality, and the DCC-GARCH model, we analyse both long-run relationships and time-varying co-movements across these commodities. The results reveal strong co-integration among base metals, and significant short-run causality particularly from Nickel, Copper, and Lead to other metals. Gold and Silver maintain high mutual correlation, reflecting their safe-haven roles, while metals like Nickel and Silver act as bridges between industrial and investment segments. DCC-GARCH estimates show that correlations intensified during market stress, reducing diversification potential. These findings suggest that India's metal markets have become increasingly integrated post-pandemic, amplifying systemic risk during global shocks. The study offers valuable insights for investors, portfolio managers, and policymakers on managing commodity price risk and designing responsive market strategies in volatile economic conditions.

Keywords: Volatility, bullions, metal commodities, spot market, GARCH

1. Introduction

Over the past few years, there has been a substantial increase in the financialization of commodity markets, driven by a surge in commodity trading. As a result, these markets have become highly interconnected. More recently, the onset of the Coronavirus pandemic has heightened uncertainty in financial markets, leading to several significant downturns in stock markets. This has caused increased volatility in stock returns globally, prompting investors to shift from equity markets to safe-haven assets like gold and commodity futures, resulting in a notable rise in commodity investments (Bouri *et al.*, 2020) [8]. The gold and metal markets have exhibited different short- and long-term effects following the crisis outbreak. Energy commodities plummeted, and suffered significant losses due to the pandemic whereas bullions show significant gain to the investors (Tang and Xiong 2012 [58], Olson *et al.*, 2014) [43]. The interconnections among gold, equity, and metal markets are of great concern to global investors because they play a crucial role in the economy and serve as a hedge against fluctuations in other markets, with gold being particularly important as a safe haven (Chen *et al.*, 2010) [10]. These three markets offer a diverse range of attractive investment opportunities, and fluctuations within them can potentially serve as early warning signals to policymakers regarding economic stability (Lombardi & Ravazzolo, 2016) [33], Furthermore, in the face of various macroeconomic risks, assets in these markets can interchangeably act as hedging instruments against such risks (Gevorkyan, 2017) [19]. Moreover, volatility can be transmitted from one instrument to another through various channels. For example, since metal used in the production and supply of various commodities, fluctuations in the metal are likely to affect gold markets through their impact on market cash flows. Additionally, rising oil prices lead to increased inflation, which boosts demand for gold and drives its price up (Elgammal *et al.* 2021) [17]. Recent events such as COVID-19 have introduced new uncertainties in global stock markets. Wang and Lee (2022) [61] examine the impact of the pandemic on global stock market returns and find a negative reaction; the impact was significantly greater for countries that condemned the invasion compared to those that remained neutral, such as China, India, and South Africa.

In the Indian scenario, although some research focuses on identifying the connections between gold, crude oil, and stock prices, some focused the volatility in gold and silver commodity alone and also non-agricultural commodity solely, these studies rarely delve into the interconnected volatility spillovers effects in the markets. Furthermore, the existing research on India is somewhat outdated. The uncertainty brought about by COVID-19 altered the dynamics of metal and gold prices, leading to increased risk aversion (Gharib *et al*, 2020; Mensi *et al.* 2020) [20, 37]. This paper seeks to address this gap by examining the interconnections among two commodity instruments as metal and bullions in India, specifically in terms of price and volatility during the COVID-19 period. Moreover, the correlations between gold-crude and metals returns have significantly intensified during the pandemic. The increased connectivity is more evident in the futures market. In summary, in both spot and futures markets, the interconnection in price and its volatility between metals and bullion returns has become considerably stronger event for the research point of view.

2. Literature Review

This section commences with a thorough examination of the literature concerning the interplay between asset markets and commodity futures in India. Lagesh *et al.* (2014) [32] previously explored the Indian market, detailing the investment dynamics among four types of commodity futures (composite, agriculture, metal, and energy) and asset markets (bonds and stocks). The study utilized DCC-GARCH to investigate the spillover effects between these components during the periods before and after the subprime crisis. The findings indicated that the conditional correlation between stocks and commodities weakened with increased stock market volatility, and the correlation between long- and short-term bonds and commodity futures also lessened during the crisis, resulting in a leveraged effect on return maximization. Singhal and Biswal (2021) [55] employed an MRS-VAR framework to analyze the temporal behavior of commodity futures with stocks (Nifty-50 index) and government securities, aiming to evaluate the efficiency of commodity futures in investment portfolios. They suggested that the optimal portfolio composition is affected by the economy's dynamic state. Roy and Roy (2017) [48] conducted an extensive analysis to assess financial contagion between composite commodity futures and asset markets (bond and gold price). Using DCC-GARCH, they observed a significant financial contagion of commodity futures with asset markets, especially the stock market. They then measured the spillover index (Diebold and Yilmaz, 2012) [16] and discovered that commodity futures receive the most volatility from gold, followed by equity and bond markets. Additionally, commodity futures act as a net transmitter of volatility to the bond, exchange rate, and gold markets, respectively. Gold, being the second most imported product after crude oil in India, has a substantial impact on the exchange rate and, consequently, the overall economy (Jain & Biswal, 2016) [26]. The concept of gold as a safe-haven or hedge, followed by silver, is well-established in investment modeling (Huang and Chang, 2021 [22]; Hussain *et al.*, 2020 [23]; Naeem *et al.*, 2021 [41], Wang and Lee, 2022) [61], particularly confirmed during the Covid-19 crisis by numerous studies (Adekoya *et al.*, 2022 [1]; Akhtaruzzaman *et al.*, 2021 [2]; Manohar and Raju, 2021 [35]; Salisu *et al.*, 2021) [49]. The decision to invest in gold is influenced by psychological biases, linked to its historical role as a currency, its value storage capability, or its reliability as a foreign reserve (Baur and McDermott, 2010) [6]. Kang *et al.* (2017) [27] investigated spillover across six commodity futures markets (including gold, silver, WTI, corn, wheat, and rice) using the multivariate DECO-GARCH and spillover index. Their research showed that gold is a net information transmitter to other commodity futures, and investors exhibit a flight-to-quality behavior during crisis periods.

Moreover, the empirical research utilized non-linear causality (Kyrtsou and Labys, 2006) [31] and DCC-GARCH to explore the lead-lag dynamics between variables and evaluate volatility transmission. The DCC-GARCH model also facilitated the determination of dynamic conditional correlations among different market pairs. It was observed that the dynamic correlation between aluminium and gold was particularly high from 2008 to 2013. Additionally, there was a brief period of negative correlation between gold and zinc, as well as between gold and copper commodities. Their results suggested that during crises, investors tend to gravitate towards safe-haven assets like gold and hold their positions until the market stabilizes. They also noted that a decrease in gold prices can lead to a depreciation of the Indian Rupee, which in turn can result in a decline in stock prices. Maitra and Dawar (2019) [34] investigated the spillover among commodity futures, stock, and exchange rates using the VAR framework followed by Granger causality. Their analysis showed that while there is no long-term relationship among the three markets, there is a unidirectional spillover from the MCX composite index to stocks. By estimating a wavelet-based DCC-GARCH model, Chakrabarty *et al.* (2015) [9] found that volatility spillover is sensitive to changes in investment horizons. Palamalai and Prakasam (2015) [45] found no evidence of a long-run cointegrating relationship between stocks and gold prices or any short-run causality. Jain and Biswal (2016) [26], using a DCC-GARCH framework, estimated non-linear causality and noted that correlations between gold prices and commodity market returns, as well as gold prices and exchange rates, were higher during the global financial crisis of 2008-2013 compared to the rest of the decade. In a more recent study post-COVID-19, Mukherjee and Bardhan (2022) [39] and Mukherjee and Bardhan (2020) [38], using daily data from 2017 to 2020, applied the ARDL model to examine the long-term movements of bonds, gold spot prices, and stock processes. They observed that before COVID, stock returns were influenced by gold and oil prices, but during COVID, the volatility of gold and stock prices, especially aluminium and copper, drove stock returns. However, there are few studies that have examined both return and volatility spillover among commodity and financial markets in India. Sendhil *et al.* (2013) [53] found persistent volatility in the spot market while assessing the efficiency of commodity futures for four agricultural commodities. Some studies have investigated volatility spillovers between spot and futures prices in the commodity market [Kumar *et al.* (2014) [30], Gupta and Varma (2015)] [21], with some finding bidirectional volatility spillover between the two markets. Hence, studies available in context to stock and commodity interaction whereas limited between commodity instrument. Therefore, this paper focuses on the interactions among metal and bullions commodity market in India during post-COVID periods as such study is rarely conducted in Indian context.

3. Research Methodology

This research derives its data from the MCX (Multi

Commodities Exchange) daily closing prices of five base metals aluminium, copper, zinc, lead, and nickel and two precious metals gold and silver. The dataset comprises time-series data spanning from December 2020 to December 2024. The study specifically focuses on assessing the volatility patterns of these metals and bullions in the post-COVID-19 period, considering the lasting economic and market fluctuations triggered by the pandemic. Given the disruptions in global supply chains, demand shifts, and changes in investor sentiment, analysing the price behaviour of these metals is crucial for understanding their stability and risk dynamics.

To achieve this objective, the study employs statistical tools as EViews for data analysis, along with its application of the Augmented Dickey-Fuller (ADF) test, the Phillips-Perron (PP) test, Johansen Co-integration test, Granger Causality test, and DCC-GARCH. These techniques help in evaluating the stationarity and volatility trends of the selected metals in the post-pandemic scenario.

Augmented Dickey-Fuller Test (ADF Test)

Ensuring the stationarity of time-series data is essential for reliable statistical modeling and econometric analysis. Since the impact of COVID-19 may have induced structural changes in metal prices, testing for stationarity is a prerequisite for accurate volatility modeling. This study employs the Augmented Dickey-Fuller (ADF) test (Schlitzer) to assess whether the closing prices of base and precious metals exhibit unit root behaviour, which would indicate non-stationarity.

The hypotheses for the ADF test are stated as follows

- **H_0:** Closing prices of the time-series data contain a unit root.
- **H_1:** Closing prices of the time-series data do not contain a unit root.

By applying the ADF test, this study ensures that the time-series data is appropriately analysed for stationarity, allowing for more robust conclusions regarding the post-pandemic volatility of these metals.

Phillips-Perron Test (PP Test)

The Phillips-Perron (PP) test serves as a complementary unit root test to ADF, accounting for heteroskedasticity and autocorrelation in the data without requiring lag-length selection. This test provides robustness in confirming the stationarity of metal price series.

The hypotheses for the PP test are

- **H_0:** Closing prices of the time-series data contain a unit root.
- **H_1:** Closing prices of the time-series data do not contain a unit root.

By using both ADF and PP tests, this study ensures a comprehensive assessment of stationarity.

Johansen Co-Integration Test

While stationarity tests determine whether the time-series data contain unit roots, the Johansen Co-integration test (Johansen & Juselius) is applied to examine whether a long-term equilibrium relationship exists among the prices of the selected metals.

The hypotheses for the Johansen Co-integration test are:

- **H_0:** There is no co-integration among the selected metals.
- **H_1:** There exists at least one co-integrating relationship among the selected metals.

This test helps understand how the prices of base and precious metals move together over time, particularly in the post-pandemic market scenario.

Granger Causality Test

To analyse the direction of causality among the selected metals, the Granger Causality test (Granger, 1969) is employed. This test helps determine whether the past values of one metal's price can predict the future values of another metal's price, providing insights into market interdependencies.

The hypotheses for the Granger Causality test are:

- **H_0:** Selected Premium Metals does not Granger-cause Selected Base Metals.
- **H_1:** Selected Premium Metals Granger-causes Selected Base Metals.

This test is crucial in identifying lead-lag relationships between base and precious metals, which can have significant implications for investors and policymakers.

By employing these statistical tests, this study ensures a rigorous examination of the volatility, co-integration, and causal relationships of base and precious metals in the post-COVID-19 era.

DCC Garch Model

To analyse the evolving interrelationships among metal prices, this study incorporates the Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroscedasticity (DCC-GARCH) model. Introduced by Engle (2002), the DCC-GARCH model is particularly effective in capturing time-varying correlations between multiple financial time series. Unlike constant correlation models, DCC-GARCH allows the strength and direction of correlations to change over time in response to market conditions. This is especially valuable when examining commodities such as metals, whose price movements are often influenced by global events, policy changes, and economic shocks. By modelling both individual volatilities and dynamic co-movements, the DCC-GARCH framework provides a more realistic and flexible approach to understanding market behavior. The DCC-GARCH model expressed as:

Conditional Covariance Matrix

- $H_t = D_t \times R_t \times D_t$
- Univariate GARCH (1,1) for individual asset variance:
- $h_{it} = \omega_i + \alpha_i \times \varepsilon_{i,t-1}^2 + \beta_i \times h_{i,t-1}$
- Dynamic Conditional Correlation (DCC) equations:
- $Q_t = (1 - a - b) \times \bar{Q} + a \times z_{t-1} \times z_{t-1}' + b \times Q_{t-1}$
- $R_t = \text{diag}(Q_t)\text{^}(-1/2) \times Q_t \times \text{diag}(Q_t)\text{^}(-1/2)$

This formulation effectively captures both individual volatility clustering and the dynamic co-movement across assets, making it a robust tool for investigating volatility spillovers in metal prices. whereby; H_t is the conditional covariance matrix, D_t is the diagonal matrix of standard deviations ($\sqrt{h_t}$), R_t is the time-varying correlation matrix, Q_t is the evolving covariance matrix of standardized residuals, z_t is the vector of standardized residuals, $\bar{Q}$ is the unconditional covariance matrix of z_t and a, b are nonnegative scalars with a + b < 1

4. Data Analysis and Interpretations

Table 1: Descriptive Statistics of 5 Base metals & 2 Precious Metals spot prices

Statistic	Aluminium	Copper	Gold	Lead	Nickel	Silver	Zinc
Mean	193.29	657.42	51033.41	171.69	1584.43	63366.79	239.02
Median	202.70	710.85	50459.00	180.50	1506.00	64931.00	232.20
Maximum	309.80	847.05	63678.00	192.70	3508.70	78200.00	381.70
Minimum	127.65	0.00	0.00	0.00	0.00	33907.00	0.00
Std. Dev.	37.40	122.99	5919.30	18.50	481.86	9040.71	49.92
Skewness	0.05	-0.999	-0.45	-2.17	0.49	-0.88	0.13
Kurtosis	2.70	3.16	7.53	15.84	2.73	3.12	3.03

Source: Author's own

Table 1 and Appendix 1 among base metals, Nickel recorded the highest mean price at ₹1,781.96, reflecting its scarcity and strong industrial demand, especially in stainless steel and battery production. Copper followed at ₹617.90, supported by its essential role in electrical and construction sectors. Zinc and Aluminium averaged ₹223.46 and ₹180.91, respectively, indicating their importance in galvanizing and lightweight applications. Lead, with the lowest mean at ₹172.72, suggests relatively lower demand and volatility.

In contrast, bullion prices were significantly higher. Gold averaged ₹47,207.01, reaffirming its status as a safe-haven asset, while Silver surpassed it with a mean price of ₹61,137.25, driven by its dual role as an investment and industrial metal. These price differentials reflect the divergent market roles of industrial versus precious metals and broader investor behaviour during the study period.

Table 2: "Augmented Dickey Fuller Test" (ADF Test)

Metal	ADF Statistic	Lag Length	1% Critical Value	5% Critical Value	10% Critical Value	Prob.	Decision
Copper	-24.179	3	-3.436384	-2.864092	-2.568181	0.0000	Reject the null hypothesis
Aluminium	-33.495	0	-3.436366	-2.864084	-2.568176	0.0000	Reject the null hypothesis
Lead	-119.345	6	-3.436401	-2.864100	-2.568185	0.0000	Reject the null hypothesis
Silver	-32.555	0	-3.436366	-2.864084	-2.568176	0.0000	Reject the null hypothesis
Gold	-20.490	5	-3.436395	-2.864098	-2.568183	0.0000	Reject the null hypothesis
Nickel	-21.213	3	-3.436384	-2.864092	-2.568181	0.0000	Reject the null hypothesis
Zinc	-26.556	2	-3.436378	-2.864090	-2.568179	0.0000	Reject the null hypothesis

Source: Author's own

To examine the stationarity of the time series data for the selected metals, the Augmented Dickey-Fuller (ADF) test was conducted. The null hypothesis of the ADF test states that the series has a unit root, indicating non-stationarity. Rejection of the null hypothesis implies the series is stationary.

As illustrated in the table 2, the ADF test statistic for all seven metals Copper (-24.17908), Aluminium (-33.49589), Lead (-19.34527), Silver (-32.55567), Gold (-20.49058), Nickel (-21.21399), and Zinc (-26.55661) is significantly less than the critical values at 1%, 5%, and 10% significance levels. Furthermore, the p-values for all metals are 0.0000, which are well below the standard alpha levels (0.01, 0.05, and 0.10). This provides strong statistical evidence to reject the null hypothesis of non-stationarity in each case.

Hence, it can be concluded that the time series data for all selected metals are stationary. This stationarity is a necessary condition for conducting further econometric analyses, such as cointegration or Granger causality tests, as it ensures the validity of the statistical inferences drawn.

Table 3: Phillips Perron Test (PP Test)

Metal	1% Level	5% Level	10% Level	Adj. t-Stat	Prob.	Result
Gold	-3.4363	-2.86408	-2.56817	-135.991	0.000	Null Hypothesis Rejected
Copper	-3.43636	-2.86408	-2.56817	-90.9976	0.000	Null Hypothesis Rejected
Aluminium	-3.43636	-2.86408	-2.56817	-33.6931	0.000	Null Hypothesis Rejected
Lead	-3.43636	-2.86408	-2.56817	-11.6771	0.000	Null Hypothesis Rejected
Zinc	-3.43636	-2.86408	-2.56817	-65.5470	0.000	Null Hypothesis Rejected
Nickel	-3.43636	-2.86408	-2.56817	-55.1059	0.000	Null Hypothesis Rejected
Silver	-3.43636	-2.86408	-2.56817	-32.5623	0.000	Null Hypothesis Rejected

Source: Author's own

Table 3 The Phillips-Perron (PP) test was conducted to verify the stationarity of the time series data for seven metals: gold, silver, copper, aluminium, zinc, lead, and nickel. The results from the Table reveal that all metal price series had significantly negative adjusted t-statistics, far exceeding the critical values at the 1%, 5%, and 10% significance levels. Additionally, the corresponding p-values were extremely low (0.0000 or 0.0001), leading to the rejection of the null hypothesis of a unit root in each case. This confirms that all the series are stationary, meaning their statistical properties remain constant over time. Establishing stationarity through the PP test provides a solid foundation for further econometric analysis such as co-integration and causality testing.

Table 4: Johansen Co-Integration Test

Date: 04/02/25 **Time:** 22:09
Sample (adjusted): 12/09/2020 12/29/2024
Included observations: 1046 after adjustments
Trend assumption: Linear deterministic trend
Series: Cl_Zinc Cl_Silver Cl_Nickel Cl_Lead Cl_Gold Cl_Copper Cl_Aluminium
Lags interval (in first differences): 1 to 4
Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	Critical Value	Prob.**
None *	0.050217	162.6269	125.6154	0.0000
At most 1 *	0.043633	108.7356	95.75366	0.0047
At most 2	0.024633	62.06938	69.81889	0.1774
At most 3	0.018107	35.98015	47.85613	0.3973
At most 4	0.007757	16.86614	29.79707	0.6499
At most 5	0.005703	8.721145	15.49471	0.3918
At most 6	0.002615	2.738527	3.841465	0.0980

Source: Author's own

The Johansen Cointegration Test was used to explore the existence of a long-run equilibrium relationship among the prices of the seven metals. The Trace Test results reveal that at least two cointegrating equations exist at the 5% level, as shown by significant trace statistics:

- **"None" hypothesis:** Trace statistic = 162.6269 (p = 0.0000)
- **"At most 1":** Trace statistic = 108.7356 (p = 0.0047)

These values exceed the corresponding critical values, indicating rejection of the null hypotheses. There is a long-term equilibrium relationship among the selected metal prices, implying that their price movements are interconnected over time despite short-term fluctuations.

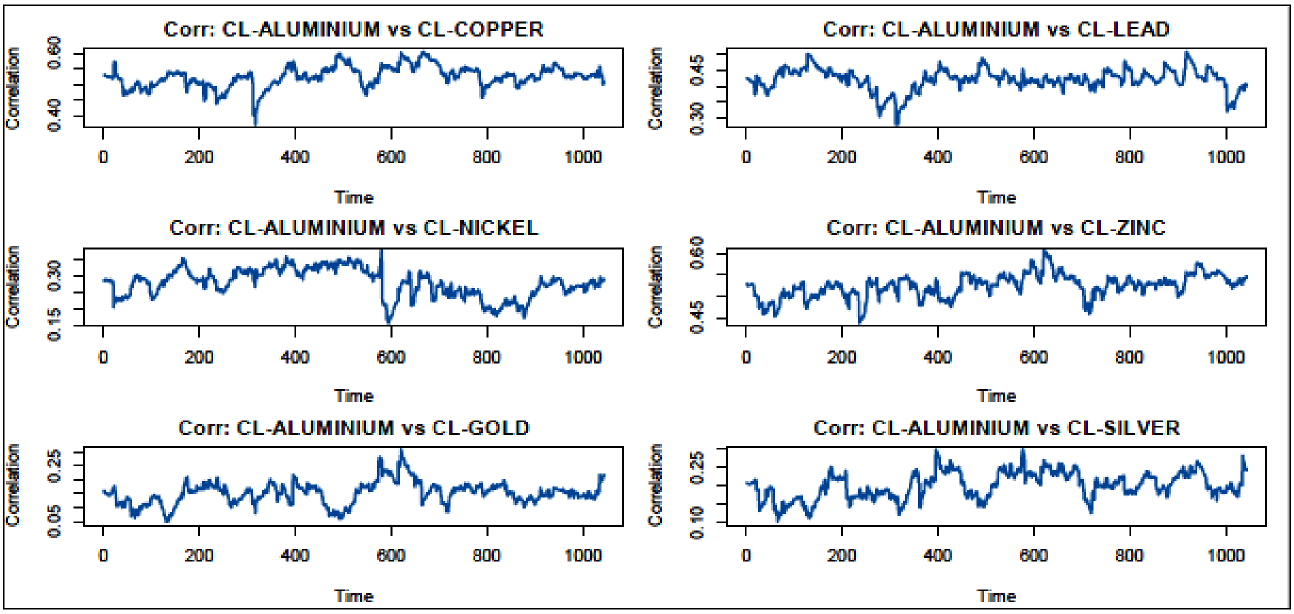
The Granger causality test (Appendix 2) revealed several statistically significant short-term relationships among the selected metals. Aluminium was found to be significantly influenced by multiple metals. For instance, copper Granger-caused aluminium with an F-statistic of 7.12 and a p-value of 0.0008, while lead's effect on aluminium was particularly strong (F = 40.21, p = 2.E-17). A bidirectional causality existed between nickel and aluminium, with nickel → aluminium (F = 5.29, p = 0.0052) and aluminium → nickel (F = 13.15, p = 2.E-06). Zinc also influenced aluminium (F = 17.17, p = 0.0038). (Appendix 2)

In the precious metals category, silver Granger-caused gold (F = 6.83, p = 0.0011), but the reverse was not statistically significant. Strong bidirectional causality was also observed between lead and copper, with lead → copper (F = 12.44, p = 5.E-06) and copper → lead (F = 37.79, p = 1.E-16). Similar mutual causality was found between nickel and lead (nickel → lead: F = 10.61, p = 3.E-05; lead → nickel: F = 22.42, p = 3.E-10) and between nickel and zinc (F = 9.09, p = 0.0001).

These results highlight the prominent roles of copper, nickel, and lead in driving short-term price dynamics among the metals studied. Their consistent causal influence across multiple relationships suggests they act as key transmission channels within the metal commodity market in the short run.

DCC GARCH

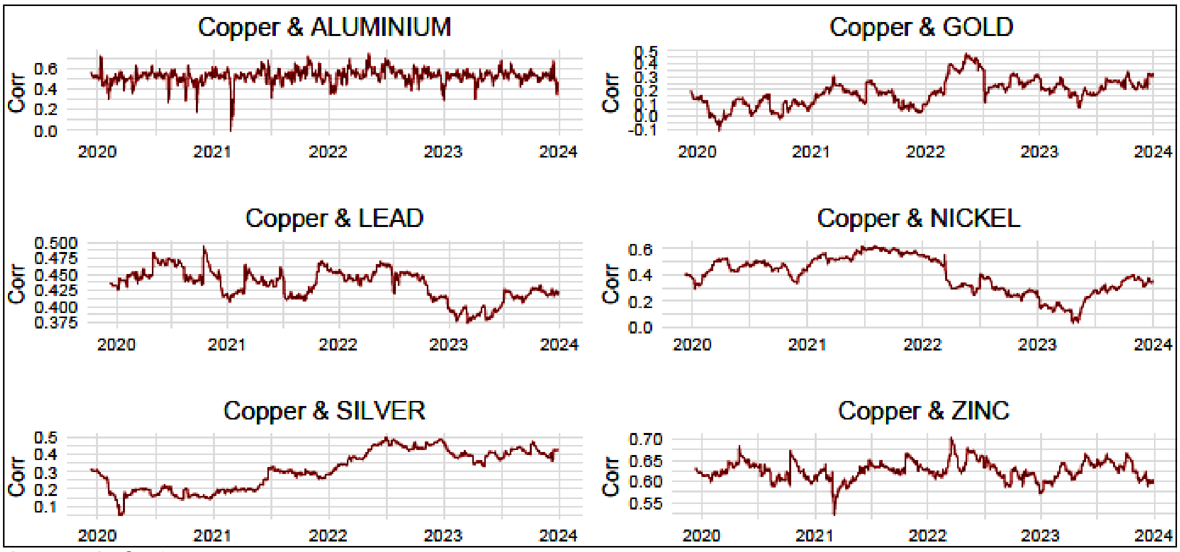
The estimation of dynamic conditional correlations (DCC) through the DCC-GARCH framework offers a nuanced understanding of how relationships among commodities evolve over time. This study investigates the interlinkages among seven major metal commodities Aluminium, Copper, Lead, Nickel, Zinc (base metals), and Gold and Silver (bullion) using daily data from 2020 to 2024. The findings unveil critical patterns in the co-movement of these commodities, highlighting the interplay between industrial demand, investment motives, and market-specific shocks.



Source: Author's own

Aluminium and Its Dynamic Linkages

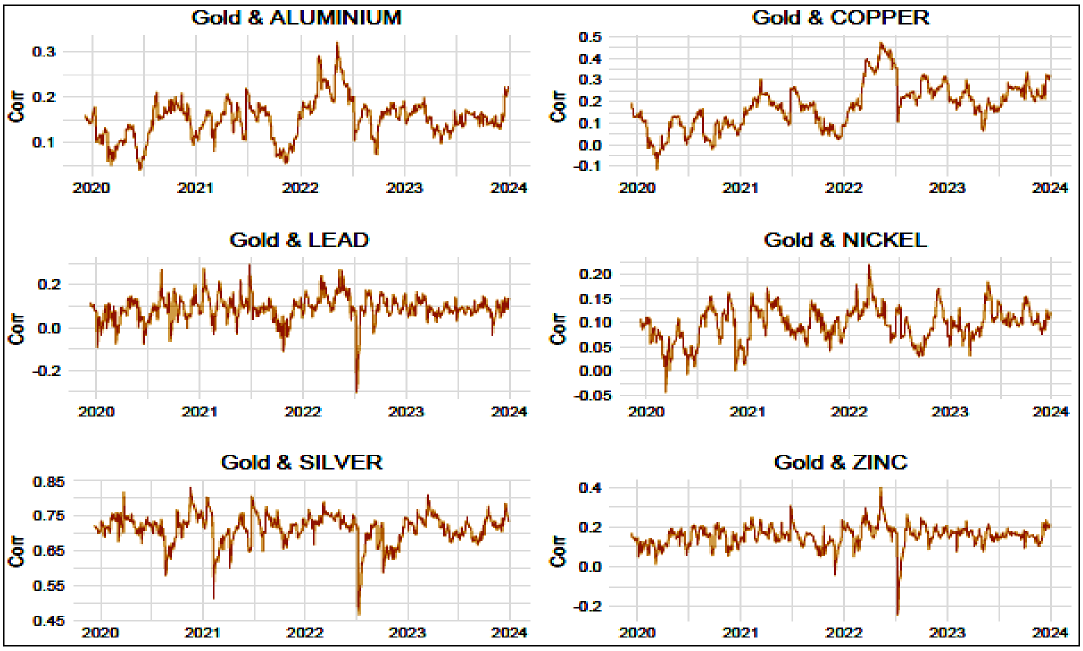
Between December 2020 and December 2024, aluminium prices witnessed notable volatility driven by factors such as post-pandemic industrial rebound, energy crises particularly in China and Europe geopolitical tensions, and the global transition towards sustainable infrastructure (IEA, 2022) [24]. The DCC-GARCH results indicate a relatively strong and time-varying correlation between aluminium and other base metals like copper and zinc, especially during 2021-2022, reflecting synchronized demand during the economic recovery and stimulus-fuelled infrastructure investment (Sehgal *et al*., 2015; World Bank, 2021) [51, 62]. Correlations with lead and nickel were moderate and fluctuating, likely due to their varying industrial use cases and supply constraints (CRU Group, 2022) [12]. Aluminium's low and stable correlation with precious metals like gold and silver underlines the divergence between industrial and investment-driven asset classes (Baur & Glover, 2012) [4]. Overall, the observed volatility and shifting correlations highlight aluminium's sensitivity to global manufacturing cycles, power costs, and policy shifts (OECD, 2023) [42], positioning it as a key industrial metal responsive to both macroeconomic momentum and supply-chain disruptions.



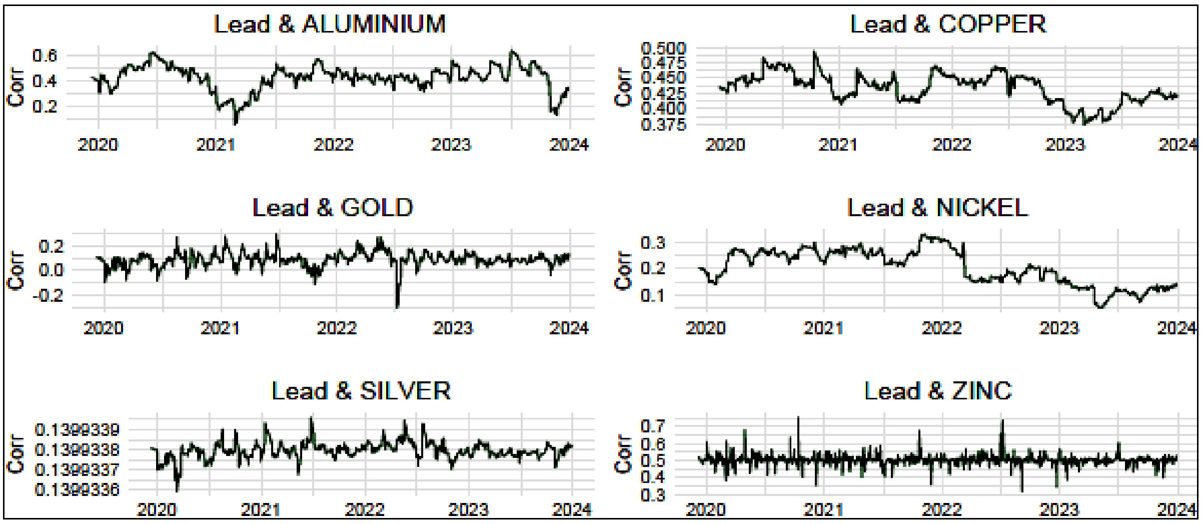
Source: Author's own

Copper as a Systemically Linked Industrial Metal

Between December 2020 and December 2024, copper experienced pronounced price volatility influenced by the global post-COVID industrial rebound, supply chain disruptions, energy shortages, and heightened demand from the electric vehicle and renewable energy sectors (IEA, 2023; IMF, 2022) [24, 25]. The DCC-GARCH analysis shows a strong and persistent correlation between copper and silver, as well as copper and zinc, especially during 2021-2022, reflecting parallel industrial demand trends (Sehgal *et al*., 2015) [51]. A moderate and time-varying correlation with aluminium and nickel suggests overlapping but distinct demand sources, particularly in infrastructure and battery manufacturing (Bloomberg NEF, 2022) [7]. The correlation with lead remained relatively stable, while its relationship with gold stayed weak, highlighting copper's role as a purely industrial metal, unlike investment-driven gold (Baur & McDermott, 2010) [6]. Overall, copper's correlation dynamics emphasize its centrality in the green transition and global manufacturing, with volatility largely driven by macroeconomic shocks, commodity super cycles, and energy market instability (World Bank, 2022) [62].

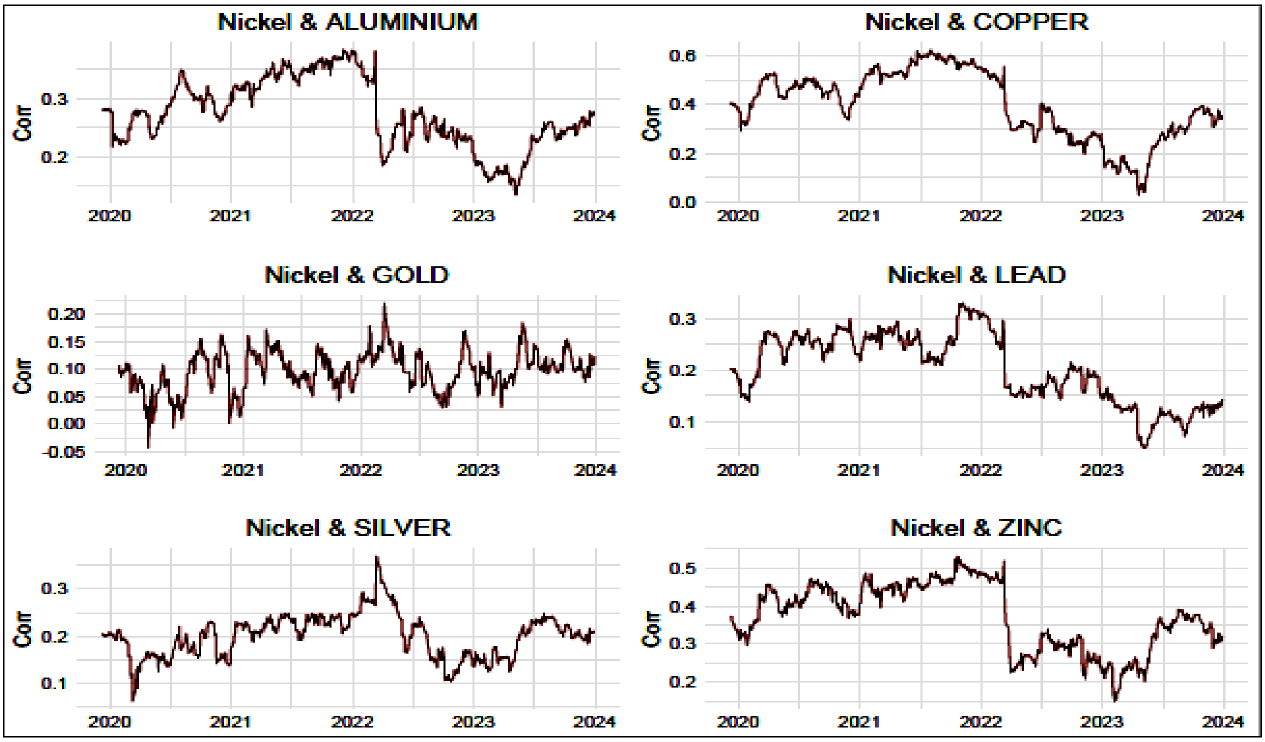


Gold: Weak Industrial Linkage, Strong Bullion Cohesion: Between December 2020 and December 2024, gold prices fluctuated notably due to global macroeconomic instability, inflationary pressures, monetary tightening by central banks, and geopolitical shocks such as the Ukraine war (IMF, 2022; OECD, 2023) [25, 42]. The DCC-GARCH results highlight a consistently strong and stable correlation between gold and silver, underscoring their joint status as investment hedges in times of crisis (Baur & Lucey, 2010; Erb & Harvey, 2006) [5, 18]. Meanwhile, correlations with industrial metals like aluminium, copper, and zinc remained low and volatile, reflecting gold's limited linkage to industrial cycles. Negative or near-zero correlations with lead and nickel further confirm gold's divergence from supply-demand-driven commodities (Sehgal *et al*., 2015) [51]. Overall, the observed dynamics reinforce gold's unique role as a safe-haven asset and inflation hedge, with its volatility and correlation patterns primarily governed by investor sentiment, interest rate expectations, and geopolitical risk (Wang & Lee, 2011) [60].

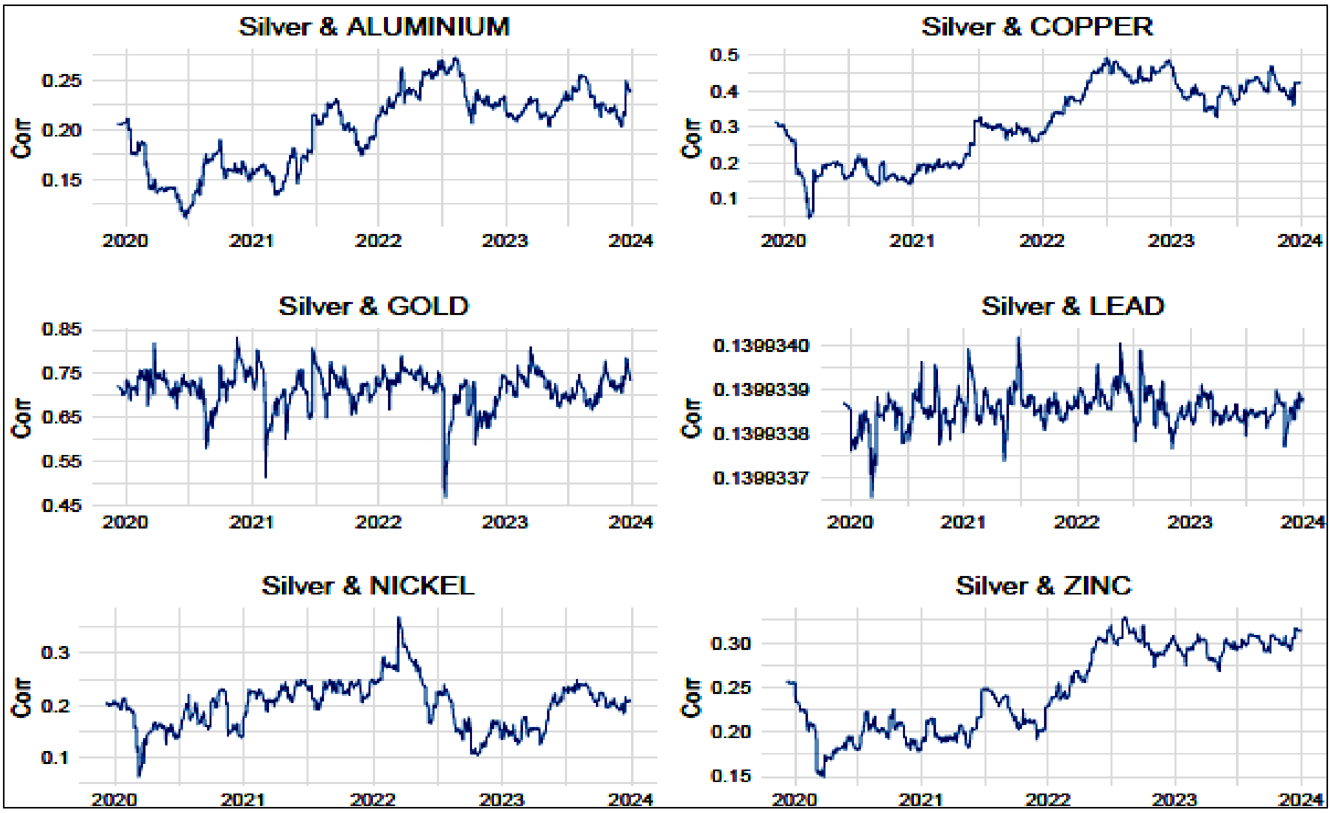


Lead: Limited Integration with Precious Metals

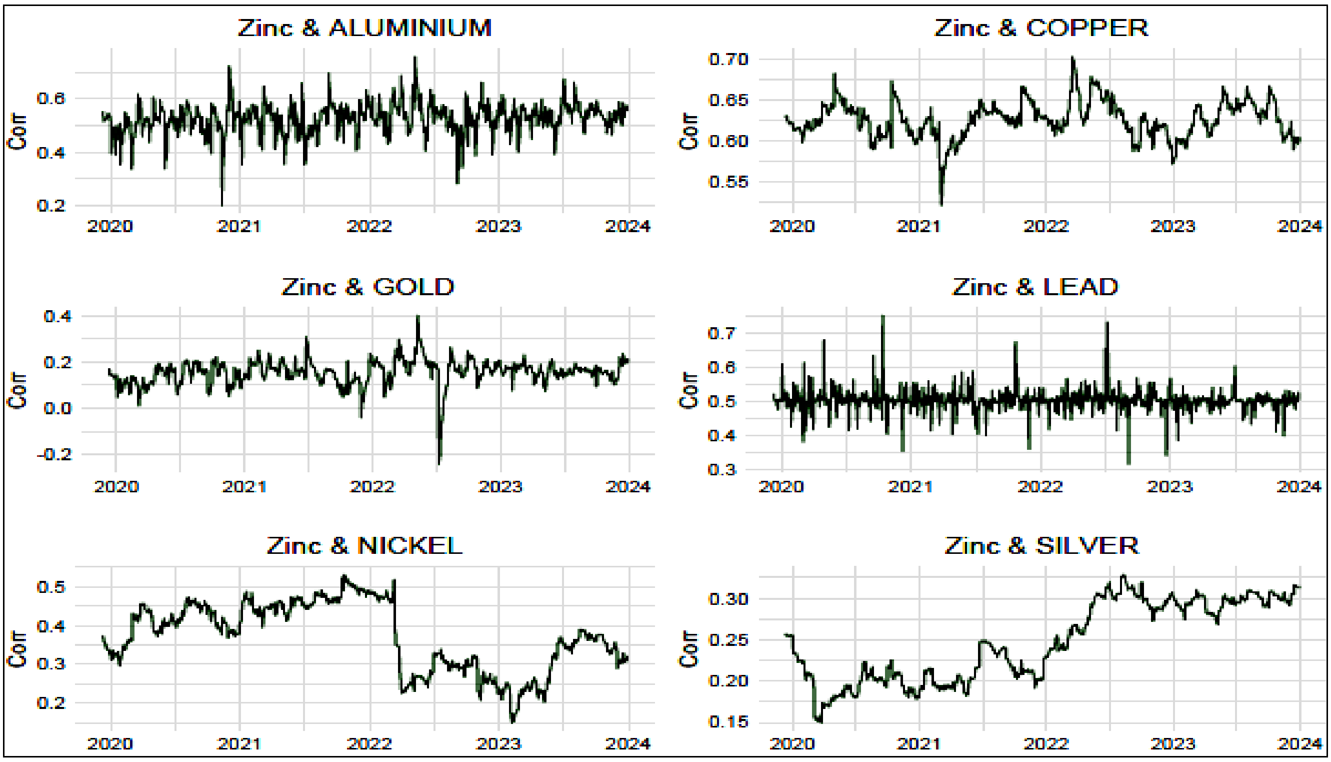
Between December 2020 and December 2024, lead prices exhibited moderate volatility driven by post-pandemic supply chain normalization, fluctuating battery demand (especially from the automotive sector), and evolving environmental regulations (CRU Group, 2022; OECD, 2023) [12, 42]. The DCC-GARCH analysis shows a consistently strong and increasing correlation between lead and silver, and a fairly stable relationship with aluminium, suggesting common industrial demand patterns, particularly during the 2021-2022 recovery period (Sehgal *et al*., 2015) [51]. Correlations with copper were weak and unstable, reflecting diverging demand drivers, while nickel and gold maintained low or static correlations due to their distinct market dynamics (World Bank, 2021) [62]. The rising correlation with zinc also signals shared influences from construction and manufacturing sectors (IEA, 2022) [24]. Overall, lead's correlation trends indicate its sensitivity to industrial production cycles and environmental compliance shifts, with its volatility shaped more by sector-specific factors than broad macroeconomic movements.



Nickel: Moderate Co-Movement Driven by Sectoral Demand: Between December 2020 and December 2024, nickel prices experienced sharp volatility driven by surging demand from electric vehicle (EV) battery production, constrained global supply, and geopolitical uncertainties especially concerning Indonesia and Russia, key suppliers (IEA, 2023; BloombergNEF, 2022) [7, 24]. The DCC-GARCH results reveal a moderately rising and stable correlation between nickel and aluminium, likely due to their shared use in lightweight manufacturing and industrial recovery (CRU Group, 2022) [12]. Correlations with silver and zinc were moderate and time-varying, reflecting overlapping industrial demand during stimulus-led growth phases (Sehgal *et al.*, 2015) [51]. However, weak and flat correlations with copper, lead, and gold point to divergent market fundamentals, especially since nickel's demand is increasingly driven by the green transition, while others respond to traditional manufacturing or investment trends (IEA, 2022) [24]. Overall, nickel's volatility and correlation patterns underscore its strategic role in energy storage technologies, with market behavior shaped largely by EV adoption rates, supply bottlenecks, and shifting global trade policies.



Silver: Bridging Industrial and Investment Characteristics: Between December 2020 and December 2024, silver prices exhibited significant volatility, primarily driven by macroeconomic disruptions, global recovery efforts post-COVID, geopolitical tensions like the Russia-Ukraine war, aggressive monetary policy shifts, and accelerating clean energy adoption (World Bank, 2021; IMF, 2022) [62, 25]. The DCC-GARCH results reveal that silver maintained a consistently high correlation with gold, reflecting their shared role as safe-haven assets during economic uncertainty and inflationary periods (Baur & Lucey, 2010) [5]. In contrast, silver's correlation with base metals like copper and nickel spiked during 2021-2022 due to synchronized industrial demand and green infrastructure push (Bloomberg NEF, 2022) [7], but later declined as central bank tightening and recessionary fears dampened industrial activity (OECD, 2023) [42]. The weaker, more erratic correlations with metals like aluminium, lead, and zinc suggest differing demand-supply dynamics and sectoral sensitivities (Sehgal *et al.*, 2015) [51]. Overall, silver's volatility and changing correlations highlight its dual role as both an industrial input and an investment asset, responding to both economic fundamentals and investor sentiment (Chong & Miffre, 2010).



Zinc: Strongest Base Metal Interdependencies

Between December 2020 and December 2024, zinc prices showed noticeable volatility influenced by global infrastructure stimulus, energy price shocks, and supply disruptions from key producers like China and Peru (World Bank, 2021; OECD, 2023) [62, 42]. The DCC-GARCH results demonstrate a strong and sustained correlation between zinc and aluminium, particularly during the 2021-2022 recovery period, reflecting their complementary roles in construction and manufacturing (Sehgal *et al.*, 2015) [51]. Zinc also maintained moderate correlations with silver and lead, consistent with shared industrial applications and synchronized demand. However, correlations with copper and nickel were weaker and more variable, indicating divergent drivers such as differing exposure to green technologies or regional production bottlenecks (IEA, 2022) [24]. Despite being a primarily industrial metal, zinc's moderate correlation with gold likely stems from overlapping macroeconomic pressures during inflationary and uncertain periods (Baur & Glover, 2012) [4]. Overall, zinc's volatility and evolving correlations underline its importance as a cyclical industrial commodity, heavily influenced by construction demand, power costs, and global policy shifts.

Findings and Conclusion

This study examined the volatility dynamics and interrelationships among seven key metals Gold, Silver, Aluminium, Copper, Nickel, Zinc, and Lead in India's post-COVID-19 commodity markets. Using ADF tests, Johansen co-integration, Granger causality, and the DCC-GARCH model, we found that all metals exhibit strong time-varying correlations, especially during pandemic-induced market stress. Gold and Silver, as traditional safe-haven assets, showed persistent volatility and a high degree of co-movement, while Nickel and Copper emerged as central nodes within the base metal segment, often Granger-causing volatility in Aluminium, Zinc, and Lead. The DCC-GARCH results revealed that the correlation structures intensified during global uncertainty, reducing portfolio diversification benefits. Volatility spillovers were especially strong from Nickel, Gold, and Silver, underlining their role as volatility transmitters in the commodity space. These findings align with past literature (e.g., Sehgal & Ahmad, 2015) [51] that emphasizes market interlinkages during systemic shocks. Overall, the post-pandemic period has increased the integration of metal markets, making them more sensitive to global disruptions. These insights are crucial for investors seeking dynamic risk management strategies and for policymakers aiming to stabilize commodity-linked sectors during future crises.

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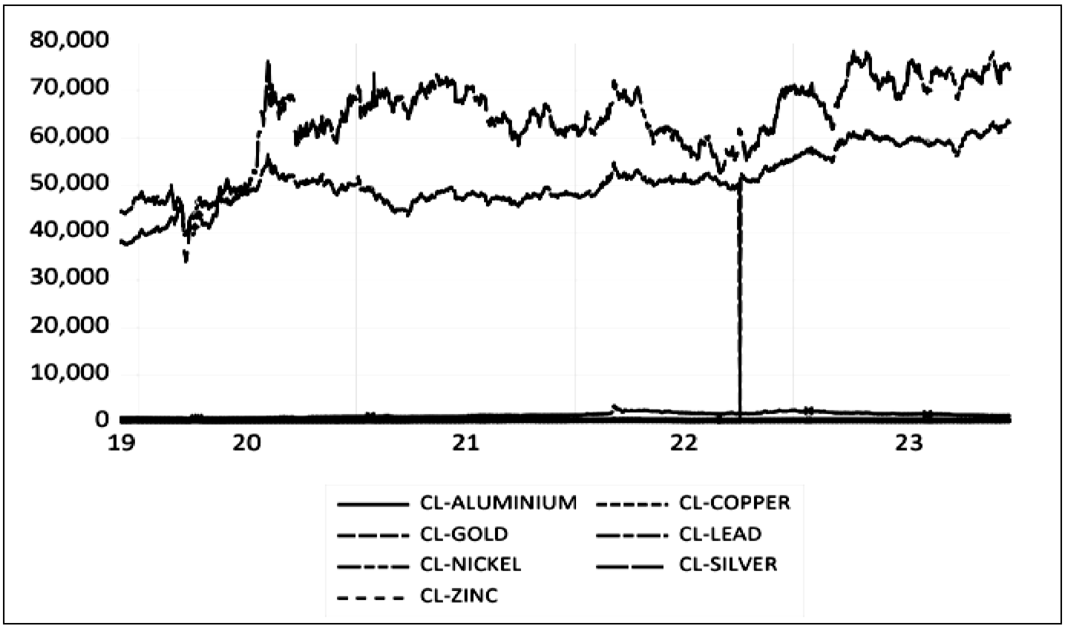
Appendix 1: Descriptive Statistics Graph:



Appendix 2

Table 5: Pairwise Granger Causality Tests

Null Hypothesis	Obs	F-Statistic	Prob.
CL_GOLD does not Granger Cause CL_ALUMINIUM	1049	0.25141	0.7777
CL_ALUMINIUM does not Granger Cause CL_GOLD	1049	2.38468	0.0926
CL_COPPER does not Granger Cause CL_ALUMINIUM	1049	0.95548	0.3850
CL_ALUMINIUM does not Granger Cause CL_COPPER	1049	7.12450	0.0008
CL_LEAD does not Granger Cause CL_ALUMINIUM	1049	0.78722	0.4554
CL_ALUMINIUM does not Granger Cause CL_LEAD	1049	40.2093	2.E-17
CL_NICKEL does not Granger Cause CL_ALUMINIUM	1049	5.29408	0.0052
CL_ALUMINIUM does not Granger Cause CL_NICKEL	1049	13.1594	2.E-06
CL_ZINC does not Granger Cause CL_ALUMINIUM	1049	1.23004	0.2927
CL_ALUMINIUM does not Granger Cause CL_ZINC	1049	17.1662	0.0038
CL_SILVER does not Granger Cause CL_ALUMINIUM	1049	0.43897	0.6448
CL_ALUMINIUM does not Granger Cause CL_SILVER	1049	0.05554	0.9460
CL_COPPER does not Granger Cause CL_GOLD	1049	2.05922	0.1281
CL_GOLD does not Granger Cause CL_COPPER	1049	0.87767	0.4161
CL_LEAD does not Granger Cause CL_GOLD	1049	2.49364	0.0831
CL_GOLD does not Granger Cause CL_LEAD	1049	6.24908	0.0020
CL_NICKEL does not Granger Cause CL_GOLD	1049	2.57456	0.0767
CL_GOLD does not Granger Cause CL_NICKEL	1049	0.23865	0.7877
CL_ZINC does not Granger Cause CL_GOLD	1049	0.28417	0.7527
CL_GOLD does not Granger Cause CL_ZINC	1049	0.03907	0.9617
CL_SILVER does not Granger Cause CL_GOLD	1049	6.83267	0.0011
CL_GOLD does not Granger Cause CL_SILVER	1049	0.97696	0.3768
CL_LEAD does not Granger Cause CL_COPPER	1049	12.4404	5.E-06
CL_COPPER does not Granger Cause CL_LEAD	1049	37.7904	1.E-16
CL_NICKEL does not Granger Cause CL_COPPER	1049	0.39618	0.6730
CL_COPPER does not Granger Cause CL_NICKEL	1049	49.1529	4.E-21
CL_ZINC does not Granger Cause CL_COPPER	1049	2.15663	0.1162
CL_COPPER does not Granger Cause CL_ZINC	1049	5.32393	0.0050
CL_SILVER does not Granger Cause CL_COPPER	1049	5.95953	0.0027
CL_COPPER does not Granger Cause CL_SILVER	1049	0.63704	0.5291
CL_NICKEL does not Granger Cause CL_LEAD	1049	10.6112	3.E-05
CL_LEAD does not Granger Cause CL_NICKEL	1049	22.4269	3.E-10
CL_ZINC does not Granger Cause CL_LEAD	1049	9.38341	9.E-05
CL_LEAD does not Granger Cause CL_ZINC	1049	2.02452	0.1326
CL_SILVER does not Granger Cause CL_LEAD	1049	15.1530	3.E-07
CL_LEAD does not Granger Cause CL_SILVER	1049	0.13555	0.8733
CL_ZINC does not Granger Cause CL_NICKEL	1049	9.09366	0.0001
CL_NICKEL does not Granger Cause CL_ZINC	1049	1.70821	0.0027
CL_SILVER does not Granger Cause CL_NICKEL	1049	3.73259	0.0243
CL_NICKEL does not Granger Cause CL_SILVER	1049	1.01387	0.3632
CL_SILVER does not Granger Cause CL_ZINC	1049	7.29780	0.0007
CL_ZINC does not Granger Cause CL_SILVER	1049	1.59465	0.2035

Date: 09/09/24 Time: 21:00
Sample: 12/02/2020 12/29/2024
Lags: 2