International Research Journal of Multidisciplinary Scope (IRJMS), 2024; 5(2): 399-412

Original Article | ISSN (O): 2582-631X DOI: 10.47857/irjms.2024.v05i02.0512

Pandemic's Ripple Effect: Exploring Dynamic Connectedness of Indian Equity and Commodity Markets

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Abstract

This research investigates volatility spillovers between the Indian equity markets and commodity futures markets. The Nifty 50 index is chosen as a representative of the equity market, based on market capitalization, while Crude Oil, Copper, Zinc, Gold, and Silver are selected to represent the commodity market in India. The selection of each commodity is grounded in considerations of liquidity and physical market size. This research investigates how the volatility in the Indian stock market interacted with the volatility of five major commodity markets throughout the COVID-19 pandemic. In order to ascertain the direction of information flow, the study employs the Granger causality approach. The research investigates how volatility transmits from the Indian equity market to various commodity markets. Employing methodologies inspired by Diebold and Yilmaz (2012) for Time Varying Parameter and Vector Autoregression (TVP VAR) analysis, the study explores these connections. To further delve into the dynamic relationship between these markets, wavelet coherence analysis is also utilized. This methodologically robust approach goes beyond traditional correlation analysis by deconstructing the co-movements across different time scales, offering a more nuanced understanding of the complex relationships and potential transmission mechanisms at play during the unprecedented period of the COVID-19 pandemic. By analyzing the frequency-dependent interactions between these markets, the study aims to shed light on how economic shocks and market fluctuations in one sector might propagate and impact the other, providing valuable insights for investors, policymakers, and researchers alike.

Keywords: COVID-19, Commodity Markets, Indian Equity Market, Volatility Connectedness.

Introduction

The World Health Organization (WHO) declared the coronavirus (COVID-19) outbreak a global pandemic on March 11, 2020 (1). By March 27, 2020, confirmed cases surpassed 500,000 and continued to rise. This unprecedented situation affected more than 170 countries, with the United States registering the highest number of confirmed cases. The ensuing economic ramifications were both significant and conspicuous. Numerous nations responded by implementing stringent quarantine measures, thereby imposing severe restrictions on economic activities. Foreseeable consequences of these measures include potential job losses and business closures, particularly within sectors such as tourism and aviation, which are anticipated to experience sustained underperformance. The Covid-19 pandemic presented significant challenges to both society and the financial system. In response to the rapid spread of the disease and its economic fallout, countries worldwide implemented social distancing measures and travel restrictions. While these precautionary measures were deemed necessary to safeguard public health, their unintended repercussions have been felt across diverse industries and businesses. These precautionary actions have had adverse effects on various industries and businesses, leading to a worldwide increase in unemployment (2).

A growing body of research has investigated the impact of pandemics like SARS and Ebola on stock market performance (3-10). Due to the severity of the epidemic, experts have started to analyze the effects of the COVID-19 pandemic and have discovered a specific trend. A recent study found that the COVID-19 pandemic significantly disrupted financial markets in 64 countries (11). Research using event studies has shown how international stock markets reacted to significant COVID-19 advancements (12, 13). These studies show a detrimental impact on financial markets. Financial markets are inherently volatile, meaning their prices fluctuate unpredictably. This uncertainty about future price movements is

(Received 17th January 2024; Accepted 25th April 2024; Published 30th April 2024)

financial risk. To assess this risk, various statistical methods are employed. Due to its impact on investment decisions and financial stability, volatility is a major concern for many participants, including individual investors, fund managers, regulators, and policymakers. Compared to past pandemics, COVID-19 has induced a surge in stock market volatility, according to a recent study (14). The extensive body of literature on the repercussions of Covid 19 highlights its global influence. While previous studies have examined how the worldwide economic crisis impacted commodities markets there has been only few studies focusing on examining the specific outcomes of the Covid 19 on Indian major commodities market (15-19). The unprecedented nature of the Covid-19 pandemic has spurred a surge in research examining its effects on various financial markets, with a particular focus on commodity markets. The evaluation of portfolio hedge ratio efficiency, value-at-risk (VaR), and optimal weightings of portfolios are some scenarios where information of market spillover effects can prove invaluable (20-22). The COVID-19 pandemic significantly increased volatility linkages between the Indian equity market and six major commodity markets. This resulted in heightened correlation, spillover effects, and contagion risk. Notably, volatility in commodity markets quickly transmitted to the Indian stock market (23). Utilizing a connectedness index to assess a four-market network, researchers discovered that developing and developed equities drive commodity markets more forcefully than vice versa in terms of both returns and volatility fluctuations (24). This study investigated the potential for volatility to spill over from the Indian stock market (represented by the BSE and NSE indices) to the commodity futures market. The DCC-GARCH model was employed to analyze the relationship between these markets. The findings suggest an absence of significant volatility transmission in the short-term. However, the possibility of volatility spillover from the stock indices to individual commodities in the long run remains open for further exploration (25). The analysis of volatility transmission between the U.S. equity market and commodity markets (including gold, oil, gas, and rice) suggests no statistically significant spillover from commodities to equities. However, under certain specific conditions, such as from oil to rice and gas, volatility spillover was observed. Additionally, the study revealed that there is no mean or volatility spillover between the gold and equity markets, suggesting that investors can mitigate portfolio risk by investing in both equities and gold (26). The impact of various commodities on equities stock markets varies. Gold has a greater influence on these markets than crude oil. Furthermore, while crude oil has a negative impact on US stock markets, it has a beneficial impact on Chinese stock markets (27). Different commodities have varying effects on equity stock markets. Gold exerts a stronger influence on these markets compared to Crude Oil. The research suggests that emerging markets experience similar spillover effects to developed markets, with volatility transmitting between the stock market and the commodities market, including prices of copper, wheat, and oil (28).

Commodity assets in investors' portfolios is expected to provide diversification benefits due to differences between the stock and commodities markets (29). A negative correlation has been identified between commodity futures and stocks, indicating potential diversification benefits for investors who include these commodities in their portfolios. This means that when stock prices decrease, commodity futures prices tend to increase, and vice versa. As a result, including commodity futures in an investment portfolio can help reduce overall risk and potentially improve returns by spreading investments across different asset classes. This finding highlights the importance of considering commodities as part of a well-diversified investment strategy (30). Research investigates the relationships between stock prices, gold prices, exchange rates, and interest rates in Pakistan's financial market. The results of the study revealed an inverse bilateral relationship between stock and gold prices. This suggests that gold can potentially function as a safe haven and an alternative investment option during periods of adverse stock price movements (31).

Examining the dynamic interplay between Indian stocks and commodity markets during the COVID-19 pandemic offers a richer understanding of the complex factors influencing market movements and investor psychology. The pandemic's onset triggered a cascading series of events, disrupting global supply chains, dampening demand, and inducing market volatility. Within this context, understanding how changes in commodity prices, such as crude oil, agricultural products, and metals, ripple through equity markets becomes paramount. For India, a net importer of commodities like crude oil and a significant producer of agricultural goods and metals, the interconnectedness between these markets is particularly pronounced. Fluctuations in commodity prices directly impact input costs for businesses, influencing their profitability and stock performance. Moreover, the pandemic-induced economic slowdown has altered consumer spending patterns and investment strategies, further complicating the relationship between equities and commodities. By examining this interdependence, researchers can uncover valuable insights into market dynamics, investor behavior, and the efficacy of policy interventions in stabilizing financial markets amidst unprecedented challenges. Additionally, exploring how this relationship evolves over time provides crucial inputs for building robust risk management frameworks and designing resilient investment portfolios capable of weathering future crises. By examining the interconnectedness of Indian stocks and commodity markets, we gain a deeper understanding of how the pandemic affected the economy. This knowledge empowers various financial players to make informed decisions.

Research in Malaysia has identified a two-way influence between stock market performance and oil prices (32). The research examined the causal links between global oil prices, precious metals (likely focusing on gold), and the exchange rate between the Indian rupee and the US dollar. The study revealed that the exchange rate doesn't exert a Granger-causal influence on gold prices (33). The researchers did not discover any significant long-term connections between the price of gold, stock prices, and the exchange rate in Indonesia (34). The study found no causal link between the stock market and gold prices, or between the exchange rate and the stock market. However, they did identify a bi-directional association between the price of gold and the exchange rate in India (35). While gold and currency fluctuations hold sway over the overall stock market in the long run, the study surprisingly found no direct influence of gold on individual stock prices. It's a complex with fascinating implications for investors and policymakers alike (36). Oil price and stock price have a Granger-causal effect on the exchange rate, the exchange rate affects foreign reserves, stock price affects oil price, and foreign reserves affect stock price (37).

Recent outbreaks, especially the COVID-19 pandemic, significantly impacted how risks spread and how the Indian stock and commodity markets are interconnected. The pandemic introduced unprecedented levels of uncertainty and risk into global financial markets, including India. Theories of risk contagion suggest that shocks in one market can quickly spread to others, especially in a highly interconnected global economy. Empirical studies during the COVID-19 pandemic have shown that the Indian stock market experienced significant turmoil, with systemic events causing widespread financial instability (38). The COVID-19 pandemic triggered a health crisis that significantly impacted stock markets worldwide. India, as a major emerging market, experienced a substantial decline of around 40% in the value of its key stock indices (39). This heterogeneity in the impact across sectors indicates the varied nature of shock spread within the economy. During the pandemic, research indicated that there was a negative and significant impact on oil prices and stock market performance, while gold prices saw a positive and significant effect (40). This suggests that the commodities market, particularly gold, served as a safe haven during the stock market downturn, highlighting the interdependence between these markets. The epidemic has underscored the importance of understanding the complex interplay between different financial markets. It has shown that shocks can rapidly transmit across markets, and the interdependence between equities and commodities can influence the overall stability of the financial system. Policymakers and investors must consider these dynamics for effective risk management and to safeguard against future systemic crises.

According to the review of the literature, various studies have been undertaken to explore volatility spillover in equity and commodity markets. GARCH, connection index and wavelet analysis were among the models used by the researchers. The vector autoregressive moving average GARCH, DCC-GARCH and BEKK GARCH are some of the multivariate GARCH models employed.

The extant body of research has thus far omitted a comprehensive exploration of crucial dimensions pertaining to volatility spillover from equities to commodity markets within the Indian financial landscape during the period of the COVID-19 pandemic. The present investigation seeks to make noteworthy contributions on multiple fronts. Initially, it scrutinizes novel empirical evidence concerning volatility spillover within the realm of Indian liquid commodities. Subsequently, it employs the Granger causality framework to delineate the directional flow of information. Thirdly, the study undertakes an examination of the shock impulse response between the equities and commodity markets through the utilization of the Vector Error Correction Model (VECM). Finally, it delves into the analysis of volatility spillover between equities and commodity markets utilizing the Time-Varying Parameter Vector Autoregressive Diebold Yilmaz 12 (TVP VAR DY12) spillover index. This research paper focuses on the spillover of volatility in Indian equity and commodity markets for two main reasons. Firstly, commodity prices have experienced significant and unexpected fluctuations in recent years, leading to increased volatility. Secondly, the equity market itself is highly volatile, prompting many investors and portfolio managers to seek diversification opportunities across different markets. This study aims to provide valuable insights for academia, investors, and portfolio managers regarding the potential benefits of diversification. If one market transmits volatility to another during the specified period, it suggests that diversification may not be effective. On the other hand, if there is no significant transmission of volatility, diversifying funds becomes a viable strategy. To better understand how each market functions within the larger system, especially regarding the transmission of volatility, we utilize a Time-Varying Parameter Vector Autoregressive (TVP-VAR) connectivity model. This approach offers a key advantage over traditional VAR models with fixed parameters. Unlike fixed-parameter models that assume constant relationships within a defined window, TVP-VAR allows the model's coefficients to adapt over time, capturing the dynamic nature of market interactions. This feature allows the model to react quickly to various events, including economic, financial, and political crises. By analyzing spillover effects, the model can identify patterns in how information transmits, providing valuable insights for investors and policymakers.

The remaining sections are structured in the following manner. Section 2 presents a comprehensive analysis and interpretation of the collected data. Section 3 outlines the method employed in the present investigation. The findings of the study are analyzed and discussed in Section 4, whereas the conclusion of the study and potential avenues for future research are outlined in the section 5.

Methodology

The analytical framework adopted in this study leverages the closing prices of the Nifty 50 and five commodities, selected based on their liquidity and physical market size. Specifically, Crude Oil, Copper, Zinc, Gold, and Silver were chosen as proxies for representing the commodity market. The temporal scope of the dataset encompasses the period spanning from January 1, 2016, to August 10, 2023. The data, meticulously sourced from the website, *investing.com*, encapsulates significant geopolitical and macroeconomic events, including the onset of the COVID-19 pandemic and the Russian-Ukrainian war. Upon statistical examination, it is discerned that the return series across all markets manifest asymmetry and exhibit tails with greater thickness than the standard normal distribution. The skewness and kurtosis statistics serve as indicative measures of this observed departure from symmetry. Furthermore, employing the Augmented Dickey-Fuller (ADF) test, revealed that all the return series under consideration demonstrate stationarity. This empirical evidence contributes to a comprehensive understanding of the underlying statistical properties and temporal dynamics of the Indian financial and commodity markets. Firstly, data gathering involves obtaining daily or intra-daily price series of relevant equity index and key commodity prices. These datasets span a significant time period to capture various market conditions and dynamics accurately. Next, econometric modeling strategies are utilized to analyze the interdependencies and spillover effects between the markets. Techniques such as Vector Autoregression (VAR) and Vector Error Correction Models (VECM) are employed to capture the dynamic interactions between equity and commodity markets. VAR models allow for the examination of how shocks in one market affect the others over time, while VECM helps in understanding the long-term equilibrium relationships and adjustments between the markets. Moreover, Granger causality tests are conducted to assess the direction and strength of causality between equity and commodity markets. This helps in identifying whether past values of one market's volatility can predict the volatility of the other market, providing insights into the causal relationships between them. Additionally, Coherence wavelet analysis is employed to explore the time-frequency domain relationships between equity and commodity market volatilities. This technique enables the identification of periods of significant volatility spillovers and their frequency characteristics, offering a deeper understanding of the temporal dynamics of market interactions. By combining these methodological approaches, a comprehensive analysis of volatility spillover between Indian equity and commodity markets can be conducted, shedding light on the interconnectedness and dynamics of these crucial segments of the financial system.

The Granger Causality test, introduced by Clive Granger in 1969, is a statistical method used to analyze time series data and assess potential cause-and-effect relationships between variables. It focuses on whether past values of one series (let's call it X) can improve the prediction of future values in another series (Y) compared to using only past values of Y itself. In simpler terms, it checks if past changes in X help predict future changes in Y.

The Granger causality equation is a statistical model used to analyze the causal relationship between two time series variables. It is represented by the equation:

$$Y(t) = \alpha + \beta 1 Y(t-1) + \beta 2 X(t-1) + \varepsilon(t)$$

Where:

- Y(t) represents the dependent variable at time t. α is the intercept term.
- Y(t-1) is the lagged value of the dependent variable at time t-1.
- X(t-1) is the lagged value of the independent variable at time t-1.
- β1 and β2 are the coefficients representing the causal effect of the lagged values on the dependent variable.
- ε(t) is the error term or residual.

To estimate the shock impulse of Indian equity and commodity markets, we employed Vector Error Correction Model (VECM). Impulse response analysis in the context of a VECM is a technique used to study how shocks to the system affect the variables in both the short run and the long run. This analysis can help researchers understand the dynamic interactions and adjustments that occur after a shock to the system. The general form of the shock impulse response equation in a VECM is:

$$Y(t) = \Gamma 0 + \Pi Y(t-1) + \Phi 1 \Delta Y(t-1) + \Phi 2 \Delta Y(t-2) + \ldots + \Phi p \Delta Y(t-p) + \varepsilon(t)$$

where:

- ΔY(t) represents the differenced vector of endogenous variables at time t.
- Γ0 is a constant term. Π is the matrix of long-run equilibrium coefficients.
- Y(t-1), Y(t-2), ..., Y(t-p) are the lagged levels of the vector of endogenous variables.
- Φ1, Φ2, ..., Φp are the short-run adjustment coefficients.
- ε(t) is the error term.

DY12 spillover index is a statistical tool used to determine the spillover effects between different financial markets. It measures the extent to which shocks in one market affect another market. The DY12 spillover index is a method that uses a vector autoregressive (VAR) model to analyze how forecast error variance is distributed among different variables. The key idea behind the DY12 Spillover Index is to estimate the directional flow of volatility or shocks among a set of financial variables. It helps researchers and analysts understand which assets or markets are more susceptible to receiving and transmitting shocks. The spillover index is calculated using a vector autoregressive (VAR) model with time-varying parameters (TVP).

Let's denote the multivariate time series as *Yt*, where *t* represents time, and it has *N* variables. The TVP VAR model can be expressed as follows:

$$Yt = \mu t + AtYt - 1 + \varepsilon t$$

Where:

- Y_t is an N×1 vector of variables at time t.
- μ_t is an N×1 vector representing time-varying means.
- A_t is an N×N matrix of time-varying coefficients.
- ε_t is an N×1 vector of white noise residuals.

To calculate DY12 spillover index, we need to estimate TVP-VAR.

$$\Sigma t = Var(\varepsilon t F t - 1)$$

Here, F_{t-1} represents the information available up to time t−1.

Spillover Index$_t$=$\sum i=1N\sum j=1, j=iN\Sigma t, ij$

Where:

- N is the number of variables.
- Σt,ij represents the element at the i-th row and j-th column of the conditional variance-covariance matrix Σt.

Coherence wavelet analysis can be applied to the study of comovements of volatility in financial markets. Volatility comovements refer to the degree to which the volatilities of different assets move together over time. Understanding these comovements is important for risk management, portfolio diversification, and understanding systemic risk in financial markets.

The wavelet coherence can be calculated using the following equation:

$$WCOI(a,b) = |R(a,b)|^2/S\_x(a)S\_y(b)$$

Where:

- WCOI(a, b) is the wavelet coherence at scale a and time b.
- R(a, b) is the cross-wavelet transform of the two time series at scale a and time b.
- S_x(a) and S_y(b) are the wavelet power spectra of the individual time series at scale a and time b, respectively.

Results and Discussion

Table 1 is showing the summary statistics of the equity and commodity markets for different time horizons. Notably, during the pre-COVID period, all markets exhibited positive log returns. However, the COVID period witnessed negative returns for silver and crude oil, while the post-COVID period showed negative returns for copper and zinc. The standard deviation of crude oil, indicating its volatility, was notably high across all panels. A prominent observation is that commodity markets in India tend to be riskier than equity markets. During the pre-COVID period, the equity market displayed negative skewness, while commodity markets showed positive skewness, suggesting a higher likelihood of positive returns in the latter. Conversely, during the COVID period, all markets exhibited negative skewness. In the post-COVID period, silver demonstrated positive skewness. The leptokurtic nature of distribution observed across all markets implies that both equity and futures markets may generate either substantial or minimal returns in the future. To assess the stationarity of log returns, Augmented Dickey-Fuller (ADF) tests were conducted, revealing significant results for all panels. The stationary nature of log returns suggests a stable financial environment. Additionally, the presence of conditional heteroscedasticity was examined using the ARCH-LM Test. The rejection of the null hypothesis concerning the ARCH effect indicates

Table 1: Descriptive statistics

Pane1: Pre covid period						
Sum. Statistics	NIFTY	Gold	Crude oil	Silver	Copper	Zinc
Mean	0.000504	0.003678	0.005285	0.001527	0.004362	0.000616
Maximum	0.023726	2.50512	3.465504	0.701563	2.816426	0.067581
Minimum	-0.027281	-0.026732	-0.070568	-0.11902	-0.044208	-0.048316
Stdev	0.007415	0.09635	0.134187	0.032073	0.10868	0.01524
Skewness	-0.276988	25.7717	25.250697	15.127176	25.511619	0.174959
Kurtosis	1.039249	666.097965	648.192874	332.359173	657.139584	0.982171
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	679	679	679	679	679	679
ADF Test	0.01	0.01	0.01	0.01	0.01	0.01
ARCH-LM test	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Panel 2: During covid						
Sum. Statistics	NIFTY	Gold	Crude oil	Silver	Copper	Zinc
Mean	0.000629	0.000445	-0.000398	-0.000063	0.000506	0.000607
Maximum	0.084003	0.035541	0.318937	0.068856	0.039958	0.086585
Minimum	-0.139038	-0.056474	-0.345727	-0.086807	-0.066746	-0.071834
Stdev	0.013837	0.009427	0.038165	0.01436	0.011815	0.01419
Skewness	-1.722295	-0.708372	-1.415194	-0.28073	-0.538738	-0.15081
Kurtosis	20.505108	3.878498	27.889944	4.715978	2.840136	3.570332
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	745	745	745	745	745	745
ADF Test	0.00	0.00	0.00	0.00	0.00	0.00

ARCH-LM test	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Panel 3: Post covid period

Sum. Statistics	NIFTY	Gold	Crude oil	Silver	Copper	Zinc
Mean	0.000259	0.000514	0.000211	0.000451	-0.000162	-0.000805
Maximum	0.02981	0.027336	0.080855	0.06	0.043526	0.061076
Minimum	-0.04896	-0.027655	-0.118254	-0.050034	-0.04791	-0.071951
Stdev	0.009405	0.00777	0.027528	0.011031	0.011537	0.016783
Skewness	-0.430126	-0.103133	-0.616686	0.473925	-0.258361	-0.418113
Kurtosis	2.272901	1.247483	1.887654	4.102742	1.472788	2.038163
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	398	398	398	398	398	398
ADF Test	0.00	0.00	0.00	0.00	0.00	0.00
ARCH-LM test	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

the existence of conditional heteroscedasticity in the markets, highlighting potential variations in volatility over time. This comprehensive analysis provides valuable insights into the dynamics of equity and commodity markets, aiding investors and researchers in understanding market behavior and making informed decisions.

In Figure 1, the data illustrates a positive correlation between gold and crude oil during the pre-COVID period. Additionally, NIFTY demonstrates a weak correlation with silver during this time frame. Amidst the COVID-19 pandemic, NIFTY exhibits a positive correlation with all commodities except gold. Notably, gold maintains positive correlations with both silver and copper during this period. However, in the post-COVID period, the correlations between equity and commodity markets turn negative. Despite this overall trend, some commodities, such as gold to crude oil and crude oil to silver, still exhibit existing positive correlations.

The results of granger causality test for the equity and commodity market are presented in table 2. It has been used to determine how one market influences another and how much influence one market has on another (38, 39). This analysis suggests that there was no Granger causality between crude oil prices and the NIFTY stock market index before the COVID-19 pandemic. However, during the pandemic, a causal relationship emerged. Crude oil price movements Granger-caused changes in the NIFTY, and vice versa. This indicates that crude oil price fluctuations impacted the NIFTY, and the NIFTY's performance influenced zinc prices. This suggests a potential for information transmission between the equity and commodity markets during the COVID-19 period. Interestingly, the analysis reveals no such causal relationship between these markets in the post-pandemic period. Global economic recovery, stimulus measures, supply chain disruptions and investor risk perceptions are some of the reasons behind the absence of information flow (40).

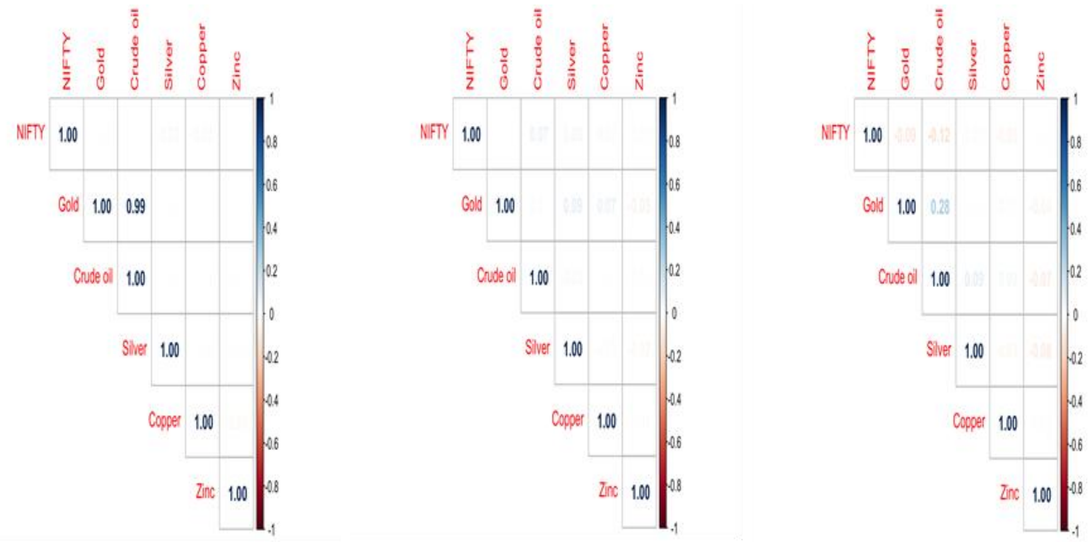

Figure 1: Correlation matrix between equity and commodity market

Table 2: Results of Granger causality

Hypothesis	**Panel 1** Pre covid		**Panel 2** During Covid		**Panel 3** Post Covid	
H0	F value	P value	F value	P value	F value	P value
No granger causality from NIFTY to Gold	0.0087	0.9258	1.8253	0.1619	2.074	0.1503
No granger causality from Gold to NIFTY	0.4391	0.5994	0.33376	0.7136	2.6019	0.1072
No granger causality from NIFTY to Crude oil	0.0012	0.9719	0.0.3439	0.7091	0.2984	0.5851
No granger causality from Crude oil to NIFTY	0.7875	0.3752	2.3078	0.0485 **	0.305	0.581
No granger causality from NIFTY to Silver	0.6422	0.4232	0.0279	0.9725	0.5374	0.4637
No granger causality from Silver to NIFTY	0.0763	0.7825	2.1621	0.1158	0.3198	0.5719
No granger causality from NIFTY to Copper	0.0083	0.9274	0.4062	0.6663	0.7235	0.3953
No granger causality from Copper to NIFTY	0.8035	0.3704	2.9623	0.0785	1.7254	0.1894
No granger causality from NIFTY to Zinc	3.0376	0.08181	2.5534	0.0485 **	8e-04	0.978
No granger causality from zinc to NIFTY	1.0843	0.2981	1.4571	0.2336	0.0273	0.8687

H1: There is a granger causality

Table 3 is explaining about the shock impulse response for the pre covid, during covid and post covid. Positive values suggest a positive relationship between the variables, where an increase in one variable leads to an increase in the other variable. In the pre covid, the shock impulse response in all the markets is positive except copper and NIFTY. So, the increase in the equity market leads to increase in the commodity markets and vice versa. In pre covid period, the markets are free from shocks. In the post covid period the shock impulse response is positive in most markets. During covid 19, the shock impulse response among all markets except copper and silver are negative. A negative shock refers to an unexpected decrease in market conditions or factors that can lead to a downward movement in prices or values. The combination of economic uncertainty, reduced consumer demand, supply chain disruptions, investor panic, and central bank interventions contributed to the decrease in share prices during the COVID-19 pandemic. The influence of the COVID-19 pandemic on stock returns exhibits temporal variability and is contingent upon the duration of the observation period. As the temporal window is extended, the influence of the COVID-19 pandemic shock gradually diminishes. There exist three primary factors contributing to this observed decrease in influence. In light of the worldwide dissemination of the COVID-19 pandemic, there has been an increased focus on the COVID-19 pandemic, leading to the implementation of a range of measures including lockdowns, workforce reductions, and home quarantine. In the current context, with the pandemic having become a commonplace occurrence, nations have amassed substantial knowledge in the realm of pandemic prevention and control. Consequently, their efforts in this domain have undergone continual enhancement.

Over a period of time, the emotional state of investors, characterized by panic, eventually reached a state of stability, resulting in a drop in the impact of investor mood on stock market performance. Furthermore, the COVID-19 pandemic has given rise to novel investment prospects in various sectors. Notably, the production of low-end goods like masks and high-end products such as ventilators has emerged as lucrative investment opportunities. Additionally, the pharmaceutical industry has witnessed a surge in investment due to the research and development of COVID-19 vaccines and related drugs. Similarly, the internet communication industry, particularly the cloud computing sector, has experienced a boom, leading to bullish trends in the stock market characterized by technological advancements and structural changes. Therefore, as time progressed, the adverse influence of the COVID-19 pandemic on stock market returns steadily diminished, and the markets included in the study, the pandemic even yielded a favorable impact on stock market returns.

Table 3: Shock impulse response

Panel	Panel 1: Pre COVID	Panel 2: COVID period	Panel 3: Post COVID
Shock impulse response from NIFTY to Gold	0.0387	-0.0012	-0.0010
Shock impulse response from Gold to NIFTY	0.0130	-0.0007	0.0000
Shock impulse response from NIFTY to Crude oil	0.0587	-0.0037	-0.0049
Shock impulse response from Crude oil to NIFTY	0.0206	-0.0011	0.0000
Shock impulse response from NIFTY to Silver	0.0006	-0.0006	-0.0001
Shock impulse response from Silver to NIFTY	0.0004	-0.0004	0.0000
Shock impulse response from NIFTY to Copper	-0.0221	0.0026	-0.0009
Shock impulse response from Copper to NIFTY	-0.0007	0.0026	0.0000
Shock impulse response from NIFTY to Zinc	0.0038	0.0008	-0.0003
Shock impulse response from Zinc to NIFTY	0.0017	0.0006	0.0000

The analysis of our study focused on the TVP VAR spillover index based on the DY2012 index, specifically employing a time-varying parameter VAR (TVP-VAR) model (41). Unlike other models, this approach does not necessitate a fixed length period for the moving rolling window and is robust to outliers. We can identify the optimal lag length for a TVP-VAR model by using the Bayesian information criterion (BIC). Table 4 is showing the results of Diebold Yilmaz spillover index based on TVP VAR. The findings reveals that the total connectivity index increased from 21.76% in the pre-COVID period to 24.41% during COVID and subsequently stabilized in the post-COVID period. Both the equity and commodity markets of India were significantly impacted by COVID-19. Positive values indicate information senders, while negative values signify information receivers. NIFTY, gold, crude oil, and zinc were information receivers in the pre-COVID period, while silver and copper were information senders. Copper emerged as the largest sender of spillover in the pre-COVID period, followed by crude oil and gold, whereas zinc was the weakest sender. During the COVID period, NIFTY and gold became information senders, while the other markets were recipients of volatility spillover. Markets with negative net spillovers, including crude oil, silver, and zinc, demonstrated lower resilience compared to NIFTY, gold, and copper, suggesting a robust capacity to absorb shocks. In net spillover transmitter markets, the values of gold and NIFTY were comparatively lower than that of copper, indicating higher risk for investors in copper. In the post-COVID period, there was a shift in the Indian market dynamics. NIFTY and gold, which were spillover senders during COVID, became receivers of volatility spillover. Zinc, which was a receiver in the pre-COVID and pandemic periods, turned into a sender in the post-COVID period.

Figure 2 illustrates the total connectedness of markets, showing fluctuations between 20% and 50%, except during the COVID-19 period when connectedness exceeded 75%. The overall connection index experienced a modest fall during the pandemic but gradually recovered. The dynamic total connectedness index exhibited sequential variability, increasing during market stress like the early stages of the COVID-19 pandemic. The lower price volatility observed in the post-COVID period is attributed to the pandemic's impact on the growth prospects of developing economies heavily reliant on commodity exports (42). These findings align with previous study indicating the complexity of the connectedness between equity and commodity markets (43).

Table 4: TVP VAR connectedness index

	NIFTY	Gold	Crude oil	Silver	Copper	Zinc	FROM
Panel 1: Pre covid period							
NIFTY	79.79	4.49	6.72	2.64	2.88	3.49	20.21
Gold	4.28	76.17	8.51	3.39	6.55	1.1	23.83
Crude oil	5.15	6.77	65.57	6.15	12.5	3.86	34.43
Silver	0.46	2.23	2.03	90.88	0.95	3.46	9.12

Copper	2.33	3.73	6.71	2.52	81.74	2.96	18.26
Zinc	4.05	1.72	5.31	5.48	8.17	75.28	24.72
TO	16.26	18.94	29.27	20.18	31.05	14.87	130.58
NET	-3.95	-4.89	-5.16	11.06	12.79	-9.85	21.76

Panel 2: During covid period

	NIFTY	Gold	Crude oil	Silver	Copper	Zinc	FROM
NIFTY	82.52	3.43	4.01	3.31	3.27	3.45	17.48
Gold	3.83	77.14	4.87	3.51	6.53	4.12	22.86
Crude oil	3.86	5.06	75.69	4.64	8.42	2.33	24.31
Silver	4.78	5.42	4.03	76.77	5.03	3.97	23.23
Copper	5.51	5.04	3.94	4.8	77.04	3.67	22.96
Zinc	5.02	4.69	3.15	4.23	18.54	64.38	35.62
TO	23	23.65	19.99	20.5	41.79	17.53	146.46
NET	5.52	0.78	-4.31	-2.73	18.83	-18.08	24.41

Panel 3: Post Covid period

	NIFTY	Gold	Crude oil	Silver	Copper	Zinc	FROM
NIFTY	88.16	2.17	4.16	1.96	1.82	1.74	11.84
Gold	1.93	74.94	5.07	2.21	12.98	2.87	25.06
Crude oil	2.41	4.76	69.21	3.16	18.85	1.61	30.79
Silver	2.4	2.79	2.98	85.55	2.48	3.8	14.45
Copper	1.03	4.62	2.32	4.94	84.95	2.15	15.05
Zinc	1.15	4.34	2.03	3.06	1.48	87.93	12.07
TO	8.92	18.68	16.56	15.34	37.6	12.16	109.26
NET	-2.92	-6.38	-14.23	0.89	22.55	0.09	18.21

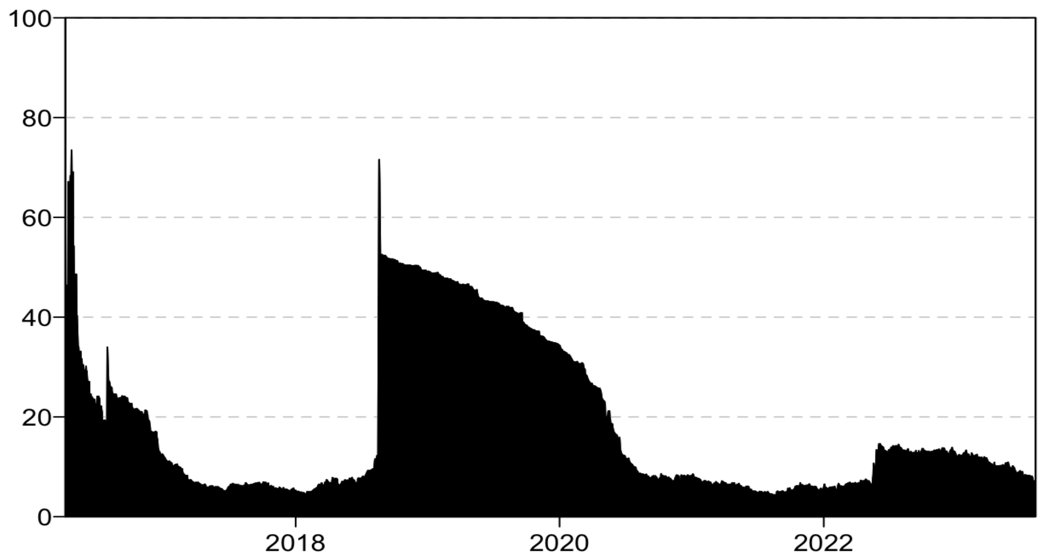

Figure 2: Total connectedness

Figure 3 illustrates the co-movements of Indian equity and commodity markets. Wavelet analysis utilizes contour plots to visualize time-frequency relationships between markets. These three-dimensional plots leverage color to represent the intensity of co-movement (strong or weak) across different time spans (horizontal axis, typically years) and frequency bands (usually not explicitly labeled). Furthermore, arrows within the plot depict the causal nature of these relationships. The arrows indicate leading and lagging relationships, along with their positive or negative direction. Similar to heat maps, these wavelet coherence plots effectively showcase the co-movement patterns between markets in the time-frequency domain. Heat maps visually represent the level of co-movement between a stock market and others in various regions. These maps use a color spectrum, where cooler tones (blue) indicate weak co-movement, and warmer tones (red) signify strong co-movement. The intensity of the color reflects the strength of the relationship, with

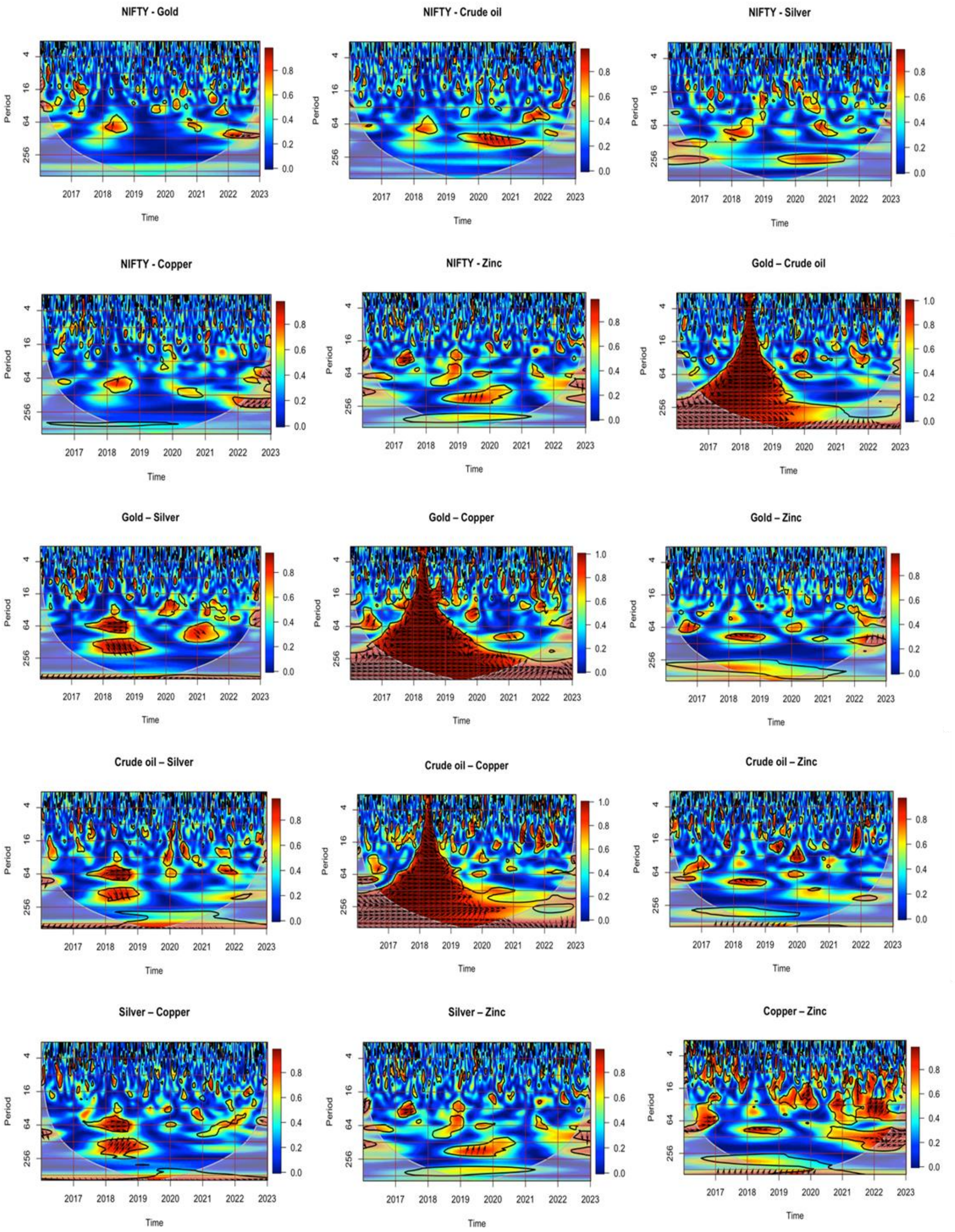

Figure 3: Market co-movements

deeper shades representing a more pronounced connection. When analyzing relationships between variables, the direction of the arrow is crucial. It indicates the potential timing between the variables. Specifically, a rightward arrow signifies a positive association, meaning the variables tend to move together. Additionally, an upward-pointing rightward arrow suggests a positive association where the first variable changes first, followed by the second variable. In contrast, a downward-pointing rightward arrow signifies a positive correlation, where the change in the second variable precedes the change in the first. Conversely, a left-pointing arrow indicates a negative correlation, meaning the variables move in opposite directions. An upward-pointing left arrow suggests a negative association where the first variable changes first, followed by the second variable. In contrast, a downward-pointing left arrow signifies a negative association where the second variable changes first, followed by the first variable. This analysis of direction helps us understand the relationship between the variables and the order in which they change.

In contrast, a downward-pointing rightward arrow signifies a positive correlation, where the change in the second variable precedes the change in the first. Conversely, a left-pointing arrow indicates a negative correlation, meaning the variables move in opposite directions. An upward-pointing left arrow suggests a negative association where the first variable changes first, followed by the second variable. In contrast, a downward-pointing left arrow signifies a negative association where the second variable changes first, followed by the first variable. This analysis of direction helps us understand the relationship between the variables and the order in which they change.

This article investigates the connections between the volatility of returns in six major commodity markets and the Indian stock market. This study makes three distinct contributions to the growing body of work examining the effects of the COVID-19 pandemic on interdependencies among various asset types. At first, the Granger causality test is employed to ascertain the transmission of information within the Indian market. In this study, the Vector Error Correction Model (VECM) is employed to analyse the shock impulse response between different markets. Additionally, the Time-Varying Parameter Vector Autoregressive (TVP-VAR) DY12 index is utilised to assess the volatility spillover in both the Indian equities and commodity markets. Our study found evidence of interdependence between the Indian equity and commodity markets during the COVID-19 period. VECM results showed that the market faced negative shocks during covid and got normalized in the post covid period. The TVP-VAR connectivity approach is employed to evaluate the extent of spillovers between different market segments, hence examining the interdependencies among markets and illustrating the effects of the COVID-19 pandemic. The findings of our study indicate that the Indian equities market, like to the global financial markets, experienced negative impacts as a result of the COVID-19 epidemic. The COVID-19 pandemic significantly impacted the relationship between the Indian stock market and global commodity markets. This resulted in increased volatility and interconnectedness between the two. Interestingly, during this period, the Indian stock market appeared to be a source of volatility for global markets. However, this influence waned over time, and the connection eventually stabilized. The selection of diversification strategies during times of crisis can be tailored to the risk preferences and market players' needs, as the advantages of diversification may vary in such circumstances. This research investigates the relationship between the Indian equity and commodity markets using wavelet analysis. Understanding how these markets move together is critical for making informed decisions about asset allocation and portfolio diversification. Traditional studies often concentrate solely on how this co-movement changes over time. However, financial markets exhibit activity at various time horizons. By employing wavelet coherence, this study explores how the co-dependence between the equity and commodity markets evolves dynamically across different time scales. The analysis aims to reveal the presence of variations in co-movement not only over time but also across different time frequencies. Additionally, the study highlights the instability of co-movement, particularly during pandemic. The results found that the co-movements among commodity markets are increased during covid 19. To delve deeper into understanding these dynamics, it's imperative to examine the influence of regulatory changes, investor behavior, and external shocks on market dynamics. Regulatory changes, such as amendments in trading rules or policies, could potentially alter market behaviors and interlinkages. Similarly, shifts in investor behavior, driven by factors like risk perception or speculative activities, might contribute to fluctuations in market volatility and spillover effects. Furthermore, external shocks, ranging from global economic events to geopolitical tensions, can have profound impacts on market dynamics, potentially amplifying or dampening spillover effects among commodities. By scrutinizing these factors, your research aims to provide valuable insights into the intricate workings of Indian financial markets and their susceptibility to various influences.

Conclusion

This research holds significant importance for different stakeholders in the stock market domain, including government bodies, investors, and policymakers. For example, the implications of this study's findings could have substantial relevance and influence on policy decisions made by governments and policymakers. The future studies can be concentrated for cross market spillovers and effective portfolio hedging (44). Also, researchers can estimate the market movements using a new sophisticated technique named coherence wavelet analysis.

Abbreviation

Nil

Acknowledgment

No

Author Contributions

All authors have accepted responsibility for the entire content of this manuscript and approved its submission.

Conflict of Interest

Authors state no conflict of interest.

Ethics Approval

Not applicable

Funding

None declared

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