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Nagendra Marisetty
Faculty, REVA Business School (RBS), REVA University, Bangalore, Karnataka, India

Corresponding Author:
Nagendra Marisetty
Faculty, REVA Business School (RBS), REVA University, Bangalore, Karnataka, India

Evaluating long-term and short-term relationships: Cointegration of NSE NIFTY with crude oil, gold, and USD/EUR currency pair

Nagendra Marisetty

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Abstract
This study examines the interrelationships between key financial assets, including NSE NIFTY, Dow Jones Industrial Average (DJI), crude oil, gold, and the USD/EUR exchange rate over the 2014–2023 period. Through correlation analysis, unit root tests, cointegration tests, and Vector Error Correction Model (VECM), the research explores both short-term dynamics and long-term equilibrium relationships. The findings reveal strong positive correlations between NSE NIFTY and both DJI and gold, indicating the influence of global economic trends and safe-haven assets on the Indian stock market. However, the correlation between NSE NIFTY and crude oil is weaker, suggesting that oil prices, while impactful on the global economy, do not directly drive stock market performance. Currency fluctuations, as captured by the USD/EUR exchange rate, have a moderate effect on NSE NIFTY, reflecting their influence on trade and capital flows.
The Johansen cointegration test and Engle-Granger cointegration regression indicate no significant long-term equilibrium relationships among the variables, suggesting that these markets, while interrelated in the short run, follow distinct long-term paths. The VECM results further emphasize the unique role of crude oil in adjusting to long-term imbalances, while NSE NIFTY, DJI, gold, and the USD/EUR exchange rate show weaker short-term adjustments. These findings highlight the importance of understanding both the short-term interdependencies and long-term divergences between financial markets, commodities, and currencies for informed investment strategies and policy decisions. Future research should consider incorporating additional macroeconomic variables to capture the evolving complexities of these relationships.

Keywords: Crude oil, DJI, Engle-granger residual cointegration, gold, Johansen cointegration, NSE NIFTY and vector error correction model (VECM)

1. Introduction
Global financial markets are intricately connected, with movements in one asset class often rippling through others. Over the past decades, the increasing globalization of trade, finance, and investment has tightened the interrelationships between various markets and assets. This phenomenon is particularly evident in the interconnected movements of stock indices, commodities, and currency markets. Understanding these relationships is crucial for investors, policymakers, and economists, as it provides insights into how different financial assets influence one another, helping to build robust investment strategies and economic policies. Among these financial assets, stock market indices such as the NSE NIFTY (India's benchmark index), Dow Jones Industrial Average (DJI), commodities like crude oil and gold, and foreign exchange markets like the USD/EUR currency pair stand out as key indicators of global economic health and investor sentiment.
One of the main questions in the study of global financial markets is how these different asset classes relate to each other over time. Do they move together in a predictable manner, or are their movements largely independent? A powerful statistical tool used to explore these long-term relationships is cointegration analysis. Cointegration focuses on determining whether a long-term equilibrium relationship exists between multiple time series variables, despite their individual short-term fluctuations. This method is especially useful for studying variables that are non-stationary on their own, but when considered together, exhibit a long-term equilibrium.
In this context, analysing the cointegration between India's NSE NIFTY and major global financial indicators such as the Dow Jones Industrial Average (DJI), crude oil, gold, and the USD/EUR exchange rate can provide valuable insights into the long-term interdependence of

these markets. India's stock market, represented by NSE NIFTY, has grown significantly in prominence, reflecting the country's rise as an economic powerhouse. With increasing integration into the global economy, it is essential to understand how India's stock market correlates with global assets, particularly during periods of economic upheaval, such as the COVID-19 pandemic or geopolitical tensions affecting oil prices.

This study's primary focus is on the evaluation of the long-term (cointegration), and short-term relationships between the NSE NIFTY and key global financial assets such as crude oil, gold, and the USD/EUR currency pair. Crude oil prices are crucial for India, as the country is one of the largest importers of oil. Any fluctuations in oil prices directly impact inflation, production costs, and corporate profits, which in turn affect the stock market. Similarly, gold is traditionally viewed as a safe-haven asset, with investors flocking to it during times of economic uncertainty. Given India's strong cultural and economic ties to gold, understanding how gold prices correlate with NSE NIFTY can offer insights into investor behaviour during volatile times. Additionally, currency markets, particularly the USD/EUR exchange rate, have a profound impact on global trade and capital flows. Fluctuations in exchange rates influence export competitiveness and affect the valuation of multinational corporations listed on the stock exchanges, including those in India.

Previous studies on cointegration between stock markets and other asset classes have yielded mixed results, with some showing strong relationships while others suggest weaker or more volatile connections. Factors such as economic crises, changes in monetary policy, geopolitical events, and supply-demand dynamics in commodity markets can disrupt the equilibrium, causing temporary deviations from long-term relationships. For instance, the COVID-19 pandemic created unprecedented disruptions in both stock and commodity markets, with sharp declines in crude oil prices, a surge in gold prices, and volatility in currency markets. These events provide fertile ground for studying how long-term cointegration relationships hold up during extreme market conditions.

In this study, the analysis of cointegration is conducted using various econometric techniques, including Johansen's cointegration test, correlation analysis, and unit root tests such as the Augmented Dickey-Fuller (ADF) test. These methods are employed to determine whether the time series data for NSE NIFTY, DJI, crude oil, gold, and the USD/EUR exchange rate share common stochastic trends over the period from 2014 to 2023. The period selected includes significant global events such as the U.S.-China trade war, the 2015-2016 oil price crash, and the economic fallout from the COVID-19 pandemic. By examining this extended period, the study aims to capture both periods of stability and volatility, providing a comprehensive view of how these markets behave over the long term.

Initial findings from the descriptive statistics indicate strong correlations between NSE NIFTY and other global financial assets, especially the Dow Jones Industrial Average (DJI) and gold prices. The correlation between NSE NIFTY and crude oil prices, while positive, is comparatively weaker, reflecting the more complex relationship between stock market performance and oil price dynamics. The correlation with the USD/EUR exchange rate is also moderate, underscoring the influence of currency fluctuations on India's stock market, though not as pronounced as other global factors like stock indices or commodities.

The Johansen cointegration test, which is employed to assess the long-term equilibrium relationships, reveals interesting insights. Despite the strong short-term correlations, the test results suggest that no significant cointegration exists between NSE NIFTY and the other variables (DJI, crude oil, gold, and USD/EUR). This finding implies that while these markets may move together over short periods, they do not maintain a stable, long-term relationship, possibly due to the differing macroeconomic factors and market dynamics influencing each variable. However, the cointegration regression results show strong long-term relationships when considering the coefficients, particularly with the DJI, oil, and gold prices. The Engle Granger Cointegration test further supports these findings, with most variables showing non-stationarity, suggesting that they follow random walks rather than reverting to a long-term mean.

The significance of these findings extends beyond academic interest. For investors, understanding the lack of long-term cointegration means that diversification across these asset classes may offer better risk management, as the assets do not move in perfect unison over the long term. For policymakers, these results highlight the need to monitor global commodity prices and currency fluctuations closely, as they have a tangible impact on stock market performance, particularly in emerging markets like India. Additionally, further research into the evolving nature of these relationships, especially during periods of economic crises, could provide more actionable insights into how global financial markets respond to shocks.

In short, evaluating the long-term and short-term relationships between NSE NIFTY, crude oil, gold, and currency markets offers valuable insights into the interconnectedness of global financial markets. While short-term correlations are evident, the lack of strong cointegration highlights the complexity and independence of each market over the long run. By employing econometric tools like cointegration analysis, this study contributes to a deeper understanding of how global financial assets influence one another, with implications for both investors and policymakers.

2. Literature Review

Long-term and short-term relationships between stock markets and various financial and macroeconomic factors has been widely studied by many researchers. This literature review explores how stock indices integrate with other financial variables, such as currencies, crude oil, gold, and various other economic indicators. It also examines the relationships between emerging and developing markets, explores different econometric tests used in the literature, and analyses these relationships during times of crisis, such as the global financial crisis and the COVID-19 pandemic. The discussion is structured around stock market relationships in various contexts, including developed and emerging economies, using both long-term and short-term frameworks.

The integration of stock markets is a central focus of many studies. Kumar and Marisetty (2023) [30] examine the Bombay Stock Exchange (BSE) SENSEX and international stock indices such as the Nikkei 225, DAX, and S&P 500. Their findings show a strong co-movement between

SENSEX and these global indices, reinforcing the notion of growing international integration in financial markets. Similarly, Rao *et al*., (2021) [31] analyze 22 global stock indices to explore their diversification potential, indicating that global stock markets have become increasingly interconnected. Additionally, Ferreira *et al*., (2019) [11] employ detrended cross-correlation methods to reveal significant long-range correlations between stock markets in major economies. In contrast, emerging markets such as India show a negative correlation with USD exchange rates. The study underscores how correlations vary between developed and emerging markets, particularly in the context of stock market integration.

Numerous studies have focused on the interlinkages between Indian stock markets and global indices, revealing significant cointegration. Deo and Prakash (2017) [6] provide a comprehensive analysis of India's National Stock Exchange (NSE) with key global markets, demonstrating long-term relationships through Johansen cointegration tests. Similarly, Subbaiyan and Sulochana (2020) [36] examined how European markets such as the CAC40, DAX, and FTSE 100 are cointegrated with the Indian Sensex over a decade, suggesting that India's integration with international markets is not limited to developed nations but also involves emerging players. Menon *et al*. (2009) [23] extended the scope by looking at how Indian markets relate to those in China, Singapore, and the U.S., further emphasizing the interconnectedness of India with both developed and emerging economies.

The relationship between stock indices and exchange rates has been examined from various perspectives. Oskooee and Saha (2015) [3] provide a comprehensive review, suggesting that while stock prices and exchange rates are often interlinked, the direction and strength of these relationships can differ. Long and Hien (2021) [20] add to this by showing the time-varying impact of inflation on gold prices and exchange rates in Vietnam. In Middle Eastern economies, Parsva and Tang (2017) [27] find bi-directional causality between stock prices and exchange rates in Iran, Oman, and Saudi Arabia. Their study, which covers data from 2004 to 2011, highlights the stability of these relationships over time. In contrast, Aydemir and Demirhan (2009) [2] investigate Turkey and find a bidirectional causal relationship between exchange rates and stock prices, with negative causality from stock indices to exchange rates and vice versa.

The relationship between stock indices and commodity prices, especially crude oil and gold, has been extensively analysed. Dinçer, Yüksel, and Uluer (2021) [8] explore the impact of the U.S.-China trade war on global oil prices, suggesting a significant relationship between geopolitical tensions and crude oil prices. Their findings, based on cointegration and causality tests, indicate that while oil prices are influenced by the trade war, other factors also contribute to their volatility. Similarly, Manasseh *et al*. (2019) [21] study the interaction between stock prices and exchange rates, using VAR-GARCH models. Their analysis suggests a significant long-term relationship between stock prices and oil prices, while gold often serves as a hedge in times of economic uncertainty. These results are crucial for international portfolio managers aiming to diversify risk.

The relationship between stock indices and other economic indicators has also attracted scholarly attention. Paramati (2011) [26] examines the relationship between stock market performance and economic growth in India, using industrial production and GDP data from 1996 to 2009. The study finds bidirectional relationships between stock prices and industrial production but unidirectional causality from GDP to stock market performance. This finding supports the "demand following" hypothesis, where economic growth leads to stock market development. Additionally, Yıldırım and Yıldırım (2019) [42] explore the relationship between energy consumption and GDP in BRICS-T countries (Brazil, Russia, India, China, South Africa, and Turkey), revealing a bi-directional causality between energy consumption and economic growth.

Emerging markets are of particular interest in understanding the global stock market dynamics. Farahani and Dastan (2013) [13] examine the impact of Islamic banks' financing on economic growth in several Middle Eastern countries, finding a significant positive correlation. Phiri (2014) [29] also investigates the relationship between financial development and economic growth in South Africa, noting asymmetric cointegration between banking activity and stock market growth. In Pakistan, Rehman (2016) [33] explores the relationship between FDI and economic growth using the VECM model, showing that FDI is driven by economic growth rather than causing it. These studies collectively suggest that emerging markets exhibit complex interdependencies between stock indices, financial development, and economic growth. Abdalla and Murinde (1997) [1] explored the interaction between stock prices and exchange rates in smaller markets such as Korea, Pakistan, and the Philippines. Their research found significant unidirectional causality from exchange rates to stock prices, indicating that currency fluctuations play a substantial role in influencing stock prices in smaller markets.

Moving beyond emerging markets, some studies explore relationships in transitioning economies. Zhao (2002) [43] focuses on the integration of Chinese futures markets with global markets, finding a growing convergence between Chinese and international markets following China's accession to the WTO. Similarly, Tanwar (2024) [37] explores the relationship between natural gas consumption and GDP in India, though finding no significant causality between the two variables. Studies focusing on smaller economies also contribute to the broader literature. For example, Michael (2018) [24] investigates the Egyptian stock market, emphasizing the role of foreign exchange market stabilization measures on stock prices. The findings highlight the critical role of currency management in influencing stock market performance in smaller, emerging economies.

The global financial crisis and COVID-19 pandemic have provided unique opportunities to study the resilience of stock markets and their relationships with other financial variables. Füss *et al*., (2005) [12] explore how hedge funds performed during the financial crisis, showing that emerging market hedge funds (EMHFs) exhibited stable long-term comovements with traditional assets. Similarly, Manasseh *et al*. (2019) [21] examine the volatility transmission effects between stock prices and exchange rates during crisis periods, revealing heightened volatility spillover effects. Verma and Rani (2016) [40] explored the cointegration among BRICS nations after the 2008 global financial crisis and found significant causality flowing from Brazil to India and India to South Korea.

Verma (2024) [41] examined how the COVID-19 pandemic

affected cointegration among major Asian stock markets. While these markets showed a strong level of cointegration pre-pandemic, the pandemic weakened these relationships, with markets slowly returning to normal post-COVID. Similarly, Das and Gupta (2021) [5] focused on the stock indices of the five most COVID-19-affected countries, concluding that there was no cointegration among these indices during the pandemic. This finding underscores the distinct economic environments in which these countries operated, despite the commonality of the global crisis.

A wide range of econometric techniques has been used to explore these relationships. Engle-Granger cointegration and Granger causality tests are commonly employed, as seen in many of the studies mentioned above, such as Oskooee and Saha (2015) [3] and Aydemir and Demirhan (2009) [2]. Other tests, such as the Vector Error Correction Model (VECM), are also prevalent in analysing long-run and short-run dynamics. Ullah *et al*. (2014) [38] apply the VECM to explore unemployment in Pakistan, finding significant cointegration between unemployment and other economic variables.

Becker, Finnerty, and Gupta (1990) [4] applied Engle-Granger methods to study the U.S. and Japanese stock markets, revealing strong correlations but limited influence from Japan on U.S. returns. This technique has been widely adopted for its robustness in detecting long-term relationships. Füss and Herrmann (2005) [12] employed Engle-Granger methodology to analyze hedge fund strategies and stock markets, highlighting the lack of long-term relationships but emphasizing the diversification opportunities across hedge funds. Wavelet analysis, as utilized by Lee (2004) [19], offers a different perspective, demonstrating price and volatility spillovers from developed to emerging markets. These diverse approaches allow researchers to capture various dimensions of stock market interdependence.

Many studies explore both long-term and short-term relationships between stock indices and other variables. Subayyal and Shah (2011) [35] examine the Karachi Stock Exchange (KSE) index and exchange rates, finding bidirectional causality in both the short and long run. Farahani and Dastan (2013) [13] also differentiate between short- and long-run relationships, finding that Islamic banks' financing has a stronger long-run relationship with economic growth than in the short run. Raza and Aravanan (2014) [32] explored the long-term and short-term relationships between stock markets and exchange rates in India, using the BSE Sensex and Nifty indices. They found no long-term cointegration, but short-term dynamics, such as unidirectional causality between stock returns and exchange rates, were significant.

While many studies find significant relationships, others show weak or no relationships. Namini (2017) [34] finds no significant relationship between stock prices and exchange rates in Iran from 1994 to 2010, indicating that financial markets may not always exhibit strong correlations. Similarly, Tanwar (2024) [37] finds no significant relationship between natural gas consumption and GDP in India, contrasting with studies that find strong linkages between energy consumption and economic growth in other contexts. Nath and Verma (2003) [25] studied South Asian stock markets, particularly India, Singapore, and Taiwan, and found no long-term equilibrium or cointegration among these indices. This lack of significant cointegration suggests that markets in the region still operate relatively independently, offering potential for diversification. Similarly, Valadkhani and Chancharat (2007) [39] examined Thailand's stock market, finding no long-term relationships with other major global indices. This absence of cointegration highlights the potential for investors seeking opportunities outside highly integrated markets.

The relationship between stock indices and various financial and macroeconomic factors, such as exchange rates, crude oil, gold prices, and economic growth, is complex and varies across different markets and time periods. Both long-term and short-term dynamics are evident, with developed markets generally showing stronger integration compared to emerging and smaller economies. The use of diverse econometric techniques, such as cointegration and Granger causality tests, has enabled researchers to uncover these relationships, which are often influenced by external events like geopolitical tensions, financial crises, and pandemics. While significant relationships are common, some studies also reveal weak or no correlations, highlighting the importance of market-specific factors.

3. Methodology

The data for this research spans from 2014 to 2023 and includes daily price indices of NSE NIFTY, DJI, Crude Oil, Gold, and the USDEUR currency pair. The dataset provides a broad perspective on global market trends, commodity prices, and currency fluctuations. Data for NSE NIFTY and DJI are sourced from their respective stock exchanges, while Crude Oil and Gold prices are obtained from commodity markets. USDEUR exchange rates are gathered from financial data platform Yahoo Finance, ensuring accurate and reliable historical information for analysis.

The 2014–2023 period is selected to capture recent economic trends and market behaviour during a decade marked by significant global events. This timeframe includes the recovery from the 2008 financial crisis, the rise of new monetary policies, geopolitical tensions, the COVID-19 pandemic, and subsequent economic recovery efforts. Analysing this period provides a comprehensive view of how key markets, commodities, and currency pairs responded to these dynamic global factors, offering valuable insights into long-term trends and structural changes.

The selection of NSE NIFTY, DJI, Crude Oil, Gold, and USDEUR is based on their significant influence on global and domestic markets. NSE NIFTY and DJI represent major stock indices from India and the U.S., providing insights into equity market movements. Crude Oil and Gold are critical commodities that affect inflation, trade balances, and economic growth. USDEUR reflects currency exchange dynamics, crucial for understanding global capital flows and foreign exchange market trends.

3.1 Tests

3.1.1 Descriptive Statistics

Descriptive statistics provide a summary of the data, including measures like mean, standard deviation, skewness, kurtosis, and IQ range, to capture the central tendency and variability of the selected indices and currency pair. These statistics help in understanding the overall distribution and behaviour of each variable over the 2014-2023 period.

3.2. Visual Analysis

Visual analysis through charts such as line plots helps

identify trends, patterns, and anomalies in the selected indices and currency pair over time. It provides a clear depiction of movements, volatility, and correlations between variables during the 2014-2023 period.

3.3. Pearson's Correlation

Pearson's correlation among the selected variables measures the strength and direction of linear relationships between indices like NSE NIFTY, DJI, Crude Oil, Gold, and USDEUR. This analysis reveals how closely these variables move together, highlighting potential interdependencies or inverse relationships.

3.4. Unit Root Test

The Augmented Dickey-Fuller (ADF) test (1979) and the Kwiatkowski, Phillips, Schmidt, Shin (KPSS) test (1992) are commonly used for testing stationarity. The ADF test is often criticized because its inability to reject the null hypothesis of a unit root may result from low power against alternatives that are weakly stationary. In contrast, the KPSS test assumes stationarity as the null hypothesis and tests it against the alternative of a unit root. To conduct the ADF test, a regression model is estimated to check for the presence of a unit root.

Regression Model as follows

$$\Delta X_t = \alpha + \beta X_{t-1} + \sum_{j=1}^{k} \gamma_j \, \Delta X_{t-j} + \varepsilon_t \quad (1)$$

In this context, the difference operator is denoted as Δ, which represents the change in the series. Therefore, if X is the series being tested, then $\Delta X_t = X_t - X_{t-1}$ is the first difference of the series. The variable k refers to the number of lagged differences included in the regression model to account for potential autocorrelation in the error term.

KPSS Test statistics is

$$\eta_u = T^{-2} \sum \left(\frac{S_t^2}{S^2(L)} \right) \quad (2)$$

Where

$$S_t = \sum_{i=1}^{t} e_t$$

$$S^2 = T^{-1} \sum_{i=1}^{t} e_t +$$

$$2T^{-1} \sum_{s=1}^{L} \left(1 - \frac{s}{L+1}\right) \sum_{t=s+1}^{T} e_t e_{t-s}$$

In this context, S_t represents the partial sum process of the residuals e, while T denotes the total number of observations in the dataset. Additionally, L indicates the lag length used in the analysis.

3.5. Cointegration Tests and Vector Error Correction Model (VECM): Assess the existence of a long-run relationship between exchange rates and stock prices by employing a cointegration test. Cointegration indicates that a combination of the variables can be stationary, despite each individual variable being non-stationary. If cointegration is established among the variables, we can further explore the short-run dynamics between the series using a Vector Error Correction Model (VECM). The concept of cointegration was first introduced by Granger (1981) [14] and further elaborated by researchers such as Engle and Granger (1987) [9], Engle and Yoo (1987) [10], Phillips and Ouliaris (1990) [28], and Johansen (1988) [15], Johansen (1991) [16], and Johansen (1995) [17], among others. In this study, Johansen cointegration and Engle and Granger Residual techniques are employed to assess the number of cointegrated equations.

3.6. Johansen Cointegration Test

The Johansen cointegration method provides specific test statistics, outlined below:

$$\text{Trace} = -T \sum_{i=r+1}^{k} \ln(1 - \lambda_i) \quad (3)$$

$$\lambda_{max} = -T \ln(1 - \lambda_{r+1}) \quad (4)$$

3.7. Engle-Granger Cointegration Test

The Engle-Granger cointegration approach elucidates the long-run relationship between two variables. The first step in this analysis involves determining the order of integration for each series. Next, the cointegration equation is identified using the Ordinary Least Squares (OLS) method. In the final step, the residuals obtained from the OLS regression are tested for stationarity at levels.

Cointegration Regression Model as follows

$$y_t = \beta_0 + \beta_1 x_t + e_t \quad (5)$$

In the next step, conduct the ADF test on the residuals (e_t) to determine whether they are stationary.

$$\Delta e_t = \beta \, e_{t-1} + v_t \quad (6)$$

3.8. Vector Error Correction Model

The Vector Error Correction Model (VECM) is a widely used method for examining both long-run and short-run relationships between variables, particularly when all variables are integrated of the same order. It describes how changes in the independent variables affect the dependent variable. The general form of the VECM is provided below.

$$\Delta y_{1,t} = \delta + \alpha \, (y_{2,t-1} - \mu - \beta \, y_{1,t-1}) + \varepsilon_{1,t} \quad (7)$$

$$\Delta y_{2,t} = \delta + \alpha \, (y_{2,t-1} - \mu - \beta \, y_{1,t-1}) + \varepsilon_{2,t} \quad (8)$$

In the above two equations, the cointegrating terms are represented by β, while the speed of adjustment is denoted by α.

4. Analysis and Findings

4.1. Descriptive Statistics

Table 1: Descriptive Statistics of NSE NIFTY, DJI, Oil, Gold, and USD/EUR Currency daily prices for the period of 2014 to 2023.

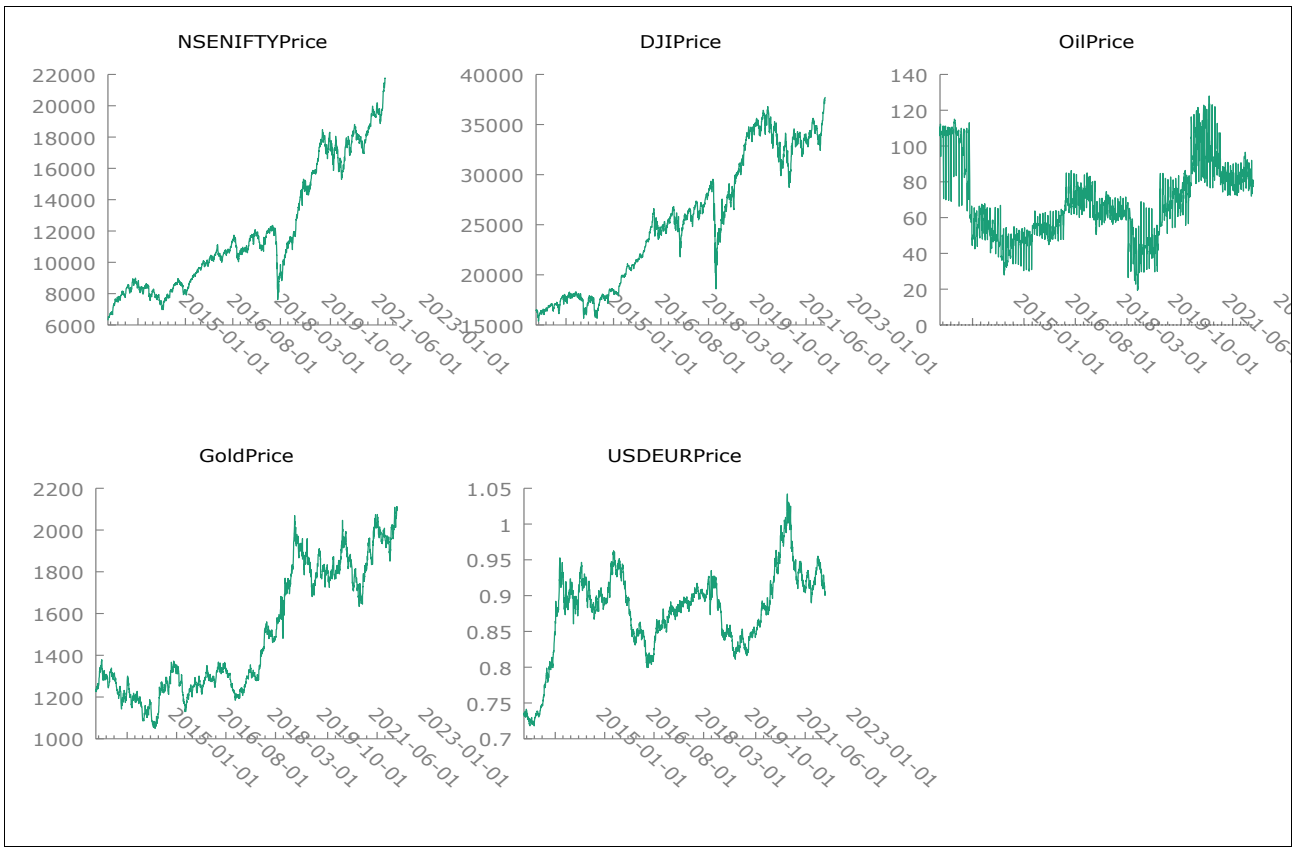
Variable	NSE NIFTY	DJI	Crude Oil	Gold	USDEUR
N	2406	2406	2406	2406	2406
Mean	12002	25336	68.401	1498.5	0.8785
Median	10807	25326	65.265	1334.7	0.8875
Minimum	6298	15373	19.33	1049.6	0.7177
Maximum	21779	37710	127.98	2112.9	1.0421
Std. Dev.	3929.6	6583	21.119	299.56	0.058813
C.V.	0.3274	0.25983	0.30875	0.19991	0.066947
Skewness	0.64163	0.12671	0.44714	0.41572	-0.65399
Ex. kurtosis	-0.94646	-1.361	-0.4262	-1.4071	0.7793
IQ range	7191.4	13852	29.893	551.85	0.068375

(***Source*:** Author's Calculations)

The descriptive statistics observed in table 1 for NSE NIFTY, DJI, Crude Oil, Gold, and USD/EUR exchange rates provide an overview of the performance and characteristics of these financial variables over the given period. With a sample size (N) of 2406 for each variable, the mean values reveal the average prices: NSE NIFTY at 12,002, DJI at 25,336, Oil at 68.401, Gold at 1498.5, and the USD/EUR exchange rate at 0.8785. The standard deviations indicate varying levels of volatility, with NSE NIFTY and DJI showing the highest levels (3929.6 and 6583, respectively), suggesting that both indices experience significant price fluctuations. In contrast, the USD/EUR exchange rate exhibits the lowest standard deviation at 0.058813, indicating more stable behaviour compared to the other variables.

Additionally, the coefficients of variation (C.V.) highlight the relative dispersion of the prices. NSE NIFTY and Oil have relatively high C.V.s of 0.3274 and 0.30875, indicating that these assets exhibit greater variability in relation to their mean prices, while the USD/EUR exchange rate has a much lower C.V. of 0.066947, reflecting its stability. The skewness values reveal that NSE NIFTY, Oil, and Gold have positive skewness, suggesting a rightward bias in their distributions with potential outliers on the higher end, while the USD/EUR exchange rate shows negative skewness, indicating a leftward bias. The excess kurtosis values for most variables being negative indicates that their distributions are flatter than a normal distribution, while the USD/EUR exchange rate's positive excess kurtosis suggests a leptokurtic distribution, indicating more frequent extreme values. Overall, these statistics suggest distinct behaviours and volatilities among the examined financial assets, reflecting their varying influences on investor sentiment and market conditions.

4.2. Visual Analysis - Time Series Trend



(***Source*:** Author's Calculations)

Chart 1: Time series trend of NSE NIFTY, DJI, Oil, Gold, and USD/EUR Currency daily prices for the period of 2014 to 2023

The analysis of the daily price charts of NSE NIFTY, Dow Jones Industrial Average (DJI), Crude Oil, Gold, and USD/EUR exchange rates from 2014 to 2023 provides significant insights into the potential cointegration and relationships among these global financial assets. Starting with NSE NIFTY, the chart shows a steady upward trend over the years, particularly gaining momentum post-2020. This reflects the growing strength of the Indian economy, with global investor confidence driving market growth. Cointegration with other indices such as DJI could suggest

that the Indian stock market is not moving in isolation but is influenced by global economic trends. This interdependence could be due to India's increasing integration into the global financial markets.

The DJI chart shows a similar upward trajectory, albeit with more pronounced fluctuations, particularly around the COVID-19 pandemic in 2020. The market shows significant dips and recoveries, in line with global economic disruptions and recoveries. The overall trend mirrors global investor sentiment and the health of the U.S. economy. In the context of cointegration, the similarity in movements between NSE NIFTY and DJI implies that global stock indices tend to move together in the long term, driven by synchronized economic cycles, trade, and investment flows. The Johansen cointegration test would likely reveal strong long-term equilibrium relationships between these two major indices.

Crude oil prices, on the other hand, show considerable volatility throughout the period, reflecting global supply-demand imbalances, geopolitical tensions, and major economic events. The significant price collapse in 2020 due to the pandemic stands out as a key event, followed by a sharp recovery. Crude oil's relationship with stock indices like NSE NIFTY and DJI can be explored in terms of cointegration. While short-term price movements in oil may seem uncorrelated to stock markets, over the long run, energy prices heavily influence production costs, inflation, and corporate profits, which eventually affect equity markets. A cointegration analysis would potentially show long-term relationships, as oil prices and stock indices often move together due to global economic conditions.

Gold prices, depicted in the fourth chart, exhibit more of a countercyclical movement compared to stock indices. Gold is traditionally considered a safe-haven asset, with prices rising during times of economic uncertainty or market downturns. This is visible during periods of stock market dips, where gold prices increased. Cointegration between gold and stock indices like NSE NIFTY and DJI may not be immediately evident due to their opposing behaviour in the short term. However, during prolonged economic crises or inflationary periods, both gold and equity markets can show some degree of cointegration as investors adjust their portfolios in response to long-term economic conditions.

The USD/EUR exchange rate shows fluctuations reflective of monetary policy differences, trade dynamics, and international capital flows. Exchange rate movements have a direct impact on global stock indices, especially for multinational companies whose revenues are dependent on currency valuations. A strong correlation between the USD/EUR exchange rate and indices like NSE NIFTY or DJI would suggest that currency risks are factored into global investment strategies. In the context of cointegration, the movement of exchange rates and stock indices could reflect global financial integration, where changes in currency values indirectly impact stock market performance through international trade and investment flows.

The analysis of these five financial assets-NSE NIFTY, DJI, Crude Oil, Gold, and USD/EUR-indicates that while they exhibit different short-term behaviours, there are likely long-term cointegrating relationships among them. Stock indices like NSE NIFTY and DJI show synchronization due to global economic integration, while crude oil and gold affect market dynamics in different ways. Exchange rates also play a crucial role in influencing stock market performance. A thorough cointegration analysis would help confirm these long-term equilibrium relationships and how global economic forces tie these assets together over time.

4.3. Pearson's Correlation Test

Table 2: Correlation matrix of NSE NIFTY with the DJI, Oil, Gold, and USD/EUR Currency pair.

Variable	NSE NIFTY	DJI	Oil	Gold	USDEUR
NSE NIFTY	1	0.9307*	0.3184*	0.8915*	0.3333*
DJI	0.9307*	1	0.2741*	0.8580*	0.2911*
Oil	0.3184*	0.2741*	1	0.2262*	-0.248*
Gold	0.8915*	0.8580*	0.2262*	1	0.1867*
USDEUR	0.3333*	0.2911*	-0.248*	0.1867*	1

(***Source*:** Author's Calculations) (* Significance @ 5% level)

The correlation table 2 reveals strong relationships between NSE NIFTY, DJI, Gold, and USD/EUR prices, with a more moderate correlation to Oil prices. NSE NIFTY has a high positive correlation with the Dow Jones Industrial Average (DJI) at 0.9307, suggesting that both stock markets tend to move in the same direction over time, driven by similar global economic conditions and investor sentiment. This strong connection highlights how India's stock market is influenced by the U.S. market, reflecting shared drivers like global liquidity, interest rates, and international trade policies. NSE NIFTY also exhibits a strong positive correlation with gold prices (0.8915), indicating that both tend to rise during periods of uncertainty, as Gold serves as a safe-haven asset, and emerging markets like India benefit from risk-averse global capital inflows.

In contrast, the correlation between NSE NIFTY and Oil prices is much weaker, at 0.3184, suggesting that while there is some relationship, it is not as strong. This weaker correlation could be due to the fact that oil prices are influenced more by global supply-demand dynamics, geopolitical tensions, and energy policies, which do not always directly impact stock market movements in the same way as macroeconomic indicators do. Interestingly, the correlation between NSE NIFTY and the USD/EUR exchange rate is also moderate at 0.3333. This suggests that while currency fluctuations impact the Indian market, particularly in terms of trade and capital flows, they are not as significant a driver of stock price movements as global stock indices or commodity prices like Gold. Overall, the table illustrates that global financial markets and commodities like Gold are key factors influencing NSE NIFTY, while Oil and currency prices play a more secondary role.

4.4. Unit Root Test Constant with Trend

Table 3: Unit root test constant with trend for NSE NIFTY, DJI, Oil, Gold, and USD/EUR currency pair

Variable	At Level				First difference			
	ADF	*p-value*	*KPSS*	*p-value*	*ADF*	*p-value*	*KPSS*	*p-value*
NSE NIFTY	-1.7182	0.7435	3.6576	<0.01	-17.7093*	0.0000	0.0428	>0.10
DJI	-0.6208	0.8637	0.9341	<0.01	-15.5609*	0.0000	0.0238	>0.10
Oil	-2.5022	0.3271	2.8737	<0.01	-13.3922*	0.0000	0.0150	>0.10
Gold	-2.2828	0.4428	3.0358	<0.01	-9.96000*	0.0000	0.0298	>0.10
USDEUR	-2.4944	0.3309	1.4431	<0.01	-10.0915*	0.0000	0.0742	>0.10

(***Source*:** Author's Calculations) (* Significance @ 5% level)

The unit root test table 3 evaluates the stationarity of key variables like NSE NIFTY, DJI (Dow Jones Industrial Average), Oil, Gold, and USDEUR exchange rates. At the level, none of the variables show stationarity based on the Augmented Dickey-Fuller (ADF) test, as their p-values are all above 0.05, meaning the null hypothesis of a unit root cannot be rejected. For instance, NSE NIFTY has an ADF statistic of -1.7182 with a p-value of 0.7435, indicating non-stationarity. Similarly, the KPSS test shows p-values less than 0.01 for all variables, confirming the presence of a unit root, suggesting these series are non-stationary at the level.

When first differences are taken, all variables become stationary. The ADF test results show strong evidence against the null hypothesis of a unit root, with significant p-values across the board. For example, NSE NIFTY has an ADF statistic of -17.7093 and a p-value of 0.0000, while Oil has a statistic of -13.3922 with the same p-value. The KPSS test results at the first difference show p-values greater than 0.10, confirming the stationarity of the variables. Thus, while these variables are non-stationary at the level, they become stationary after first differencing, making them suitable for further analysis like cointegration and VECM.

4.5. Johansen Cointegration Test

Table 4: Johansen Cointegration Test (Lag order 5) for NSE NIFTY, DJI, Oil, Gold, and USD/EUR Currency.

Rank	Eigenvalue	Trace test	p-value	Lmax test	p-value
0	0.0128850	63.117	[0.1517]	31.216	[0.0995]
1	0.0053919	31.901	[0.6210]	13.013	[0.8754]
2	0.0051244	18.888	[0.5117]	12.366	[0.5255]
3	0.0026976	6.5217	[0.6388]	6.5020	[0.5573]
4	0.0000000	0.0196	[0.8884]	0.0196	[0.8884]

(***Source*:** Author's Calculations) (* Significance @ 5% level)

The Johansen Cointegration Test results in table 4 indicate the presence of no significant cointegration relationships between NSE NIFTY, the Dow Jones Industrial Average (DJI), Oil, Gold, and the USD/EUR exchange rate. Starting with rank 0, the Trace test statistic of 63.117 and the p-value of 0.1517 suggest that the null hypothesis of no cointegration cannot be rejected. Although the Lmax test statistic for rank 0 (31.216) approaches the significance threshold (p-value = 0.0995), it still fails to meet the conventional 5% significance level. This implies that the five variables do not share a strong long-term equilibrium relationship when considered together in this framework.

As we progress to higher ranks, the evidence for cointegration weakens further. For rank 1, the Trace and Lmax tests both show high p-values (0.6210 and 0.8754, respectively), clearly failing to reject the null hypothesis that there is no cointegrating vector beyond the first rank. Similarly, at rank 2 and 3, the p-values remain high, indicating no evidence of cointegration between the stock indices, Oil, Gold, and the USD/EUR exchange rate. The lack of significant cointegration relationships suggests that while these markets may exhibit short-term correlations, they do not move in a tightly bound long-term equilibrium. This could be due to the differing market dynamics influencing each variable, such as the impact of global commodity prices on Oil, safe-haven demand driving gold prices, or currency fluctuations affected by international trade and central bank policies.

4.6. Engle Granger Cointegration Test

Table 5: The Engle Granger Cointegration Regression of NSE NIFTY with the DJI, Oil, Gold, and USD/EUR Currency pair.

Variable	Coefficient	Std. Error	t-ratio	p-value	F Stat	R Square	Adj R Square
Constant	−13441.3*	407.309	−33.00	0.0000	6798.27* (0.0000)	0.9186	0.9185
DJI	0.320382*	0.00743	43.09	0.0000			
Oil	22.44100*	1.19826	18.73	0.0000			
Gold	5.315510*	0.15602	34.07	0.0000			
USDEUR	9223.330*	437.421	21.09	0.0000			

(***Source*:** Author's Calculations) (* Significance @ 5% level)

The Engle Granger cointegration regression results in table 5 shows a strong long-term relationship between the NSE NIFTY and the other variables (DJI, Oil, Gold, and USD/EUR exchange rates). The high R-squared value of 0.9186 indicates that around 92% of the variation in NSE NIFTY prices can be explained by the combined movements of these variables, confirming the model's strong explanatory power. The F-statistic of 6798.27, with a p-value of 0.0000, indicates that the overall model is highly significant, meaning the independent variables (DJI, Oil, Gold, and USD/EUR) together have a substantial impact on NSE NIFTY prices.

Looking at the individual coefficients, all variables significantly influence NSE NIFTY, as indicated by their t-

ratios and extremely low p-values (0.0000). The DJI has a coefficient of 0.320382, meaning that a unit increase in DJI is associated with an approximately 0.32 unit increase in NSE NIFTY, reinforcing the high correlation and strong influence of the U.S. market on the Indian stock market. Oil and Gold prices also show positive and significant impacts, with coefficients of 22.44100 and 5.315510, respectively. This suggests that higher oil and gold prices tend to coincide with higher NSE NIFTY prices, likely reflecting the global economic conditions that drive both commodity prices and stock markets. Finally, the USD/EUR exchange rate has a large positive coefficient (9223.330), indicating a strong relationship, possibly due to currency fluctuations affecting global capital flows, which in turn influence stock markets like NSE NIFTY. All coefficients are statistically significant, confirming their importance in explaining NSE NIFTY's long-term behaviour.

Table 6: The Engle Granger Cointegration Unit root test with constat for NSE NIFTY, DJI, Oil, Gold, and USD/EUR Currency Pair

Variable	Estimated Value (a-1)	ADF Test Static	p Value
NSE NIFTY	0.000251406	0.39692	0.9829
DJI	-0.00072193	-0.8108	0.8156
Oil	-0.0240416	-3.96511*	0.0016
Gold	-0.00070669	-0.6894	0.8476
USDEUR	-0.00409835	-2.6015	0.0926
Residuals Cointegration	-0.0149936	-3.6614	0.2521

(***Source*:** Author's Calculations) (* Significance @ 5% level)

The Engle Granger Cointegration unit root test results in the table 6 show that most of the individual time series (NSE NIFTY, DJI, Gold, and USD/EUR) are non-stationary at their levels, as indicated by the high p-values (greater than 0.05). Specifically, the NSE NIFTY has a very high p-value of 0.9829, and the DJI and Gold also exhibit high p-values of 0.8156 and 0.8476, respectively, meaning that we cannot reject the null hypothesis of a unit root. This suggests that these indices follow a random walk and are not mean-reverting in their current forms. Oil is an exception, with an ADF test statistic of -3.96511 and a significant p-value of 0.0016, indicating stationarity and that the oil prices do not have a unit root, implying they are mean-reverting over the period examined.

The residuals from the cointegration regression show an ADF test statistic of -3.66143, which typically would suggest cointegration if the p-value were below a critical level, such as 0.05. However, in this case, the p-value of 0.2521 indicates that the residuals are not stationary at the 5% significance level. This suggests that, despite the significant relationships found in the cointegration regression, the residuals do not exhibit long-term equilibrium behaviour. Therefore, while the variables are correlated and show relationships in the short term, the lack of stationarity in the residuals implies that the indices and prices do not form a stable long-term cointegrating relationship over time. This finding contrasts with the earlier regression results, highlighting that while the individual series may influence each other, they do not necessarily move together in a long-term equilibrium.

4.7. Vector Error Correction Model

Table 7: Error Correction Terms (ECT) of NSE NIFTY, DJI, Oil, Gold, and USD/EUR

Variable	Coefficient	Std. Error	t-ratio	p-value
Δ NSE NIFTY	−0.00106910	0.000941	−1.136	0.256
Δ DJI	0.00105421	0.0009862	1.069	0.2852
Δ Crude Oil	0.0581766	0.008729	6.665	0.0001*
Δ Gold	0.00111178	0.000824	1.349	0.1774
Δ USDEUR	3.77E-05	0.0004494	0.08394	0.9331

(***Source*:** Author's Calculations) (* Significance @ 5% level)

The Vector Error Correction Model (VECM) presented in table 7 explores the long-term relationships and short-term dynamics between NSE NIFTY, Dow Jones Index (DJI), crude oil, gold, and the USD/EUR currency prices. The error correction term for NSE NIFTY has a negative coefficient (-0.00106910) but is statistically insignificant with a p-value of 0.256, indicating that NSE NIFTY does not significantly adjust towards a long-term equilibrium following short-term deviations from the included variables. This suggests that NSE NIFTY's price movements may be influenced by other factors not captured in this model or that the stock index has weaker short-term ties with the other variables included in the system.

Among the other variables, crude oil prices show a highly significant error correction term with a coefficient of 0.0581766 and a p-value of 0.0001, suggesting that crude oil prices strongly adjust towards long-term equilibrium following deviations. This indicates that oil prices are highly sensitive to the other variables in the system, possibly due to global economic dependencies on energy markets. However, the error correction terms for the Dow Jones Index (DJI), gold, and USD/EUR exchange rates are not statistically significant, with p-values of 0.2852, 0.1774, and 0.9331, respectively. This suggests that, in the short term, these variables do not significantly adjust towards long-term equilibrium based on the relationships defined in this model. These results highlight the strong role of crude oil in the system while indicating that other variables, including the DJI and gold, may respond more to external factors or exhibit slower adjustment dynamics.

5. Conclusion

The comprehensive analysis of daily price movements for NSE NIFTY, DJI, crude oil, gold, and the USD/EUR exchange rate from 2014 to 2023 reveals complex interconnections between these financial assets. The strong positive correlation between NSE NIFTY and DJI reflects their shared response to global economic trends, highlighting the influence of international markets on Indian stock performance. Gold's role as a safe-haven asset is also evident through its significant correlation with NSE NIFTY, especially during economic uncertainty. Meanwhile, the weaker correlation between NSE NIFTY and crude oil suggests that although oil prices affect broader economic conditions, they do not directly drive stock market

performance as much as other factors. The USD/EUR exchange rate influences investment flows and trade dynamics but has a more limited direct impact on stock indices compared to major financial assets like gold and the DJI.

The Johansen cointegration test shows that despite strong short-term relationships between the variables, no significant long-term cointegration exists among the indices and commodities, indicating that while they may react similarly to global economic shocks, their long-term paths can diverge. The cointegration regression highlights that variable such as DJI, oil, gold, and USD/EUR explain a substantial portion of NSE NIFTY's movements, yet the lack of long-term equilibrium suggests that these markets, while interconnected, retain distinct long-term behaviours driven by market-specific factors. This calls for a nuanced approach when interpreting short-term correlations and emphasizes the importance of understanding the independent dynamics of these markets for informed decision-making by investors and policymakers.

The VECM analysis reinforces these insights, showing that crude oil prices significantly adjust toward long-term equilibrium, indicating their pivotal role in the system. However, NSE NIFTY, DJI, gold, and USD/EUR show weaker or insignificant adjustments in the short term, suggesting slower or indirect responses to market imbalances. NSE NIFTY, in particular, may be influenced by other domestic or external factors not captured in this model, reflecting the complexity of its drivers. Overall, the VECM findings, combined with the results of the Johansen and Engle-Granger cointegration tests, underscore the importance of both short-term market interdependencies and the need to consider long-term dynamics and external influences in global financial markets. Future research should incorporate additional macroeconomic variables or advanced models to further uncover the evolving relationships between these critical financial indicators.

6. Scope for Further Research

The scope for further research on the cointegration and relationship dynamics between global financial assets, such as NSE NIFTY, DJI, Crude Oil, Gold, and USD/EUR exchange rates, is vast. Future studies could explore more granular aspects of these relationships by incorporating additional macroeconomic factors like inflation rates, interest rates, and geopolitical risks that might influence these markets differently. Additionally, expanding the analysis to include other emerging market indices or commodities could provide a more comprehensive understanding of global financial interdependencies. Researchers could also apply advanced econometric models, such as time-varying cointegration or machine learning techniques, to capture the evolving nature of these relationships over different economic cycles or stress periods, offering more predictive insights for policymakers and investors.

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