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Interconnected Stock Markets: Analysing Cointegration and Correlation among Global Stock Indices

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ABSTRACT: This study examines the long-term and short-term relationships among five major global stock indices—NSE NIFTY (India), S&P 500 (USA), FTSE 100 (UK), Hang Seng (Hong Kong), and Nikkei 225 (Japan)—over the period from 2008 to 2023. Using advanced econometric techniques such as Johansen cointegration tests, Engle-Granger residual cointegration test and the Vector Error Correction Model (VECM), the research explores the degree of interconnectedness and cointegration among these indices. The results indicate strong positive correlations between NSE NIFTY, S&P 500, and Nikkei 225, suggesting a growing synchronization of these markets due to global economic integration. Johansen's test reveals the presence of multiple long-term equilibrium relationships, affirming that despite short-term deviations, these markets tend to move together in response to global macroeconomic factors.

The analysis further highlights that the S&P 500 and FTSE 100 indices exhibit significant error correction mechanisms, underscoring their leadership role in global market dynamics. In contrast, NSE NIFTY shows a weaker adjustment toward long-term equilibrium, indicating its reactive nature to changes in other global indices, particularly the S&P 500. The study finds that while Hang Seng and Nikkei 225 are connected globally, their short-term linkages appear weaker, likely influenced by regional factors. Overall, the results emphasize the critical influence of the U.S. and Japanese markets on NSE NIFTY, with both long-term cointegration and short-term market dynamics shaping the Indian stock market's movements. This research offers key insights for investors seeking to understand global stock market interdependencies and manage portfolio risk.

KEYWORDS: Engle-Granger residual cointegration, Global stock indices, Johansen cointegration, NSE NIFTY and Vector Error Correction Model (VECM)

INTRODUCTION

The interconnectedness of global stock markets has evolved significantly over recent decades, driven by the forces of globalization, advances in technology, and the increasing integration of economies. This growing link between stock markets has reshaped the investment landscape, offering both opportunities and challenges for investors, policymakers, and businesses alike. As capital flows across borders with greater ease and speed, stock markets in different parts of the world often exhibit synchronized movements, reflecting shared macroeconomic conditions, geopolitical events, and investor sentiment. Understanding the degree of correlation and cointegration between global stock indices is crucial for anyone involved in international financial markets, particularly when it comes to crafting strategies for portfolio diversification, hedging, and risk management.

At the core of this research lies the exploration of cointegration between stock indices, a concept that provides insight into long-term equilibrium relationships between financial markets. The notion of cointegration suggests that while individual stock markets may experience short-term volatility and independent movements, their long-term trends are often influenced by common global factors. This is particularly true during periods of financial crises or global economic disruptions, such as the 2008 global financial crisis and the recent COVID-19 pandemic, which exposed the vulnerabilities and interconnectedness of markets. During such periods, markets that were previously thought to be isolated or independent often exhibit a tendency to move in tandem, revealing deeper structural relationships.

Numerous studies have investigated these co-movements and correlations, especially in emerging markets like India, which are becoming increasingly integrated with global financial systems. India's stock markets, particularly the National Stock Exchange (NSE) NIFTY and the Bombay Stock Exchange (BSE) SENSEX, have been subject to considerable external influences as foreign institutional investors (FIIs) and global market dynamics play a greater role in shaping their performance. Understanding how

Indian indices relate to major global indices such as the S&P 500, FTSE 100, Nikkei 225, and Hang Seng has become a subject of significant research interest, as these relationships provide critical insights for investors and policymakers looking to navigate an increasingly globalized financial environment.

Emerging markets, including India, are often positioned at the crossroads of developed and smaller economies, leading to mixed patterns of integration. While larger markets like the U.S., Japan, and the U.K. may drive global financial trends, smaller or frontier markets retain a degree of independence, offering unique diversification opportunities. The concept of cointegration serves as a bridge between these different types of markets, highlighting the factors that link them together and those that differentiate them. Cointegration techniques, such as the Johansen and Engle-Granger methods, are instrumental in quantifying these relationships, offering a deeper understanding of how stock markets across the globe are connected in both the short and long term.

The role of crises, particularly the 2008 financial crisis and the COVID-19 pandemic, has become a focal point in analysing stock market relationships. During such periods, traditional market dynamics are often disrupted, with correlations between markets either weakening or strengthening in unpredictable ways. For instance, while the 2008 crisis revealed deep connections between developed economies, the COVID-19 pandemic exhibited varying levels of impact on stock markets worldwide, especially in emerging economies. Studies have shown that in times of global turmoil, markets that were previously segmented may begin to move together, as investors reassess risk and flight to safety becomes a common strategy. Conversely, other research points to a breakdown in cointegration during these times, as local economic conditions and responses to the crisis create divergences between markets.

This study aims to delve into these interconnected relationships by focusing on the co-movements and cointegration between key global indices, particularly NSE NIFTY, S&P 500, FTSE 100, Hang Seng, and Nikkei 225. By employing advanced econometric techniques such as the Augmented Dickey-Fuller (ADF) test for stationarity and Johansen's cointegration test, this research investigates whether these markets exhibit long-term equilibrium relationships and how short-term deviations from this equilibrium are corrected. Additionally, the analysis considers the implications for investors, particularly in terms of portfolio diversification and the potential for mitigating risks through exposure to less correlated markets.

In doing so, the research contributes to the growing body of literature on global market integration, shedding light on the dynamic and complex nature of stock market relationships in an increasingly interconnected world. The findings hold particular relevance for investors seeking to balance their portfolios by capitalizing on both the benefits of global integration and the unique characteristics of individual markets. By examining both long-term cointegration and short-term market dynamics, this study offers a comprehensive view of the global financial system's inner workings, with a particular focus on how crises impact market linkages and the role that emerging markets play in the broader global context.

LITERATURE REVIEW

The interconnectedness of stock markets across the globe has garnered significant attention in recent years, particularly with the emergence of new economic powers and the impact of global events such as financial crises and pandemics. This literature review synthesizes various studies that explore the co-movements, causal relationships, and integration of stock indices across different regions, emphasizing the implications for portfolio diversification and risk management.

Numerous studies have focused on the interlinkages between Indian stock markets and global indices, revealing significant cointegration. Deo and Prakash (2017) provide a comprehensive analysis of India's National Stock Exchange (NSE) with key global markets, demonstrating long-term relationships through Johansen cointegration tests. Their research highlights how India's market is increasingly influenced by international trends, a finding supported by Kumar and Marisetty (2023). The latter discovered that India's Bombay Stock Exchange (BSE) SENSEX has strong co-movements with indices like Nikkei 225, DAX, and the S&P 500, stressing the growing global influence on Indian stock market dynamics.

Similarly, Subbaiyan and Sulochana (2020) 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) 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.

Emerging markets, especially within the BRICS nations, have shown significant levels of cointegration. Ghulam and Joo (2024) focus on stock indices within BRICS countries, using Value at Risk (VaR) to capture the downside risk. Their findings reveal strong interdependence, particularly Brazil's significant influence on the rest of the BRICS nations. This co-movement highlights the ripple effects of one emerging market on others, suggesting that while emerging markets can offer diversification benefits, they are increasingly intertwined. Thomas et al. (2017) studied Asia-Pacific's emerging and frontier markets, like China, Thailand, Sri Lanka, and Pakistan. They found that despite some integration, these markets are relatively segmented, offering opportunities for global investors looking to diversify their portfolios. This segmentation, in contrast to the interconnectedness of BRICS, underscores the complexity and diversity within emerging markets.

Research on the relationship between emerging and developed markets has often highlighted varying levels of cointegration, particularly post-globalization. Verma and Rani (2016) 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. This finding is crucial because it illustrates how the dynamics between emerging markets themselves are evolving, especially with increased capital flows between them. Marisetty (2017) examined the Indian stock market's behaviour after liberalization and globalization in 1991, revealing how foreign investments have fostered closer ties between India and developed markets. This growing relationship between emerging and developed markets marks a shift from earlier periods of isolation, where these markets were mostly driven by local factors. Tripathi and Sethi (2010) finds significant integration between India and the US stock indices, while no integration is observed with Japan, the UK, and China. Batareddy et al. (2012) finds evidence of a single long-run cointegration relationship, indicating that emerging markets are increasingly converging with the US market. The results suggest that domestic and external factors influence stock market behaviour, with stronger linkages between Asian emerging markets and the US compared to intra-regional connections. This research contributes to the literature on market integration in Asia.

Smaller emerging markets often display unique behaviours compared to larger economies. Abdalla and Murinde (1997) 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. Papavassiliou (2014) investigates capital market integration between the Montenegrin stock market and various European Union countries and the USA, the results indicate a long-run equilibrium between Montenegro and developed Western European countries and the USA, while short-run dynamics suggest that Montenegro primarily follows an autonomous path, influenced by domestic factors. Özdemir (2020) further examined asymmetric causality relationships between developed and smaller emerging markets, revealing weaker overall correlations between them. This weak linkage suggests that smaller markets, while influenced by global events, still retain a level of independence, offering diversification opportunities for investors who seek to reduce risk exposure.

When it comes to equity mutual funds and stock markets, Pojanavatee (2014) found strong cointegration between mutual funds and the stock market in the long run. This relationship is crucial for investors looking to hedge against short-term market fluctuations. The study demonstrated how mutual fund prices move in tandem with stock indices over the long term but may diverge in the short run, offering insights into how mutual funds can be used for portfolio diversification. Chow et al. (2018) investigate the effects of the Shanghai–Hong Kong Stock Connect on the financial integration between the Hong Kong stock market and the Shanghai and Shenzhen stock markets in mainland China. Utilizing cointegration tests and both linear and nonlinear Granger causality techniques, the study reveals a growing influence of the Chinese stock markets on Hong Kong post-scheme introduction, marked by increased cointegration between their market capitalizations and indices.

The global financial crisis and the COVID-19 pandemic have profoundly impacted stock markets worldwide, altering pre-existing relationships. Verma (2023) 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) 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. Five emerging Asian economies: China, South Korea, India, Indonesia, and Taiwan, observed weakened integration post-COVID-19, with only South Korea and China maintaining short-term linkages after the pandemic, while the pre-COVID period exhibited stronger unidirectional and bidirectional causal relationships (Bhardwaj et al. 2022).

Different cointegration techniques have been used to explore market linkages, each offering unique insights. Becker, Finnerty, and Gupta (1990) 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) 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), 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. Rao et al. (2021) employing multivariate analysis, the research aims to provide insights into the relationships between different stock markets, aiding investors and portfolio managers in making informed decisions.

In contrast to studies that emphasize interdependence, some research has shown a lack of significant cointegration among markets. Nath and Verma (2003) 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) 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.

Lastly, the integration between stock indices and other asset classes such as mutual funds, hedge funds, and currencies has been a focal point of many studies. Hilliard (1979) explored the co-movement of stock prices and other asset classes during major global events, finding that currencies and stock prices often move in tandem. Similarly, Agmon (1972) research highlighted the interconnectedness of equity markets with hedge funds, suggesting that global market events affect a wide range of asset classes, not just stock indices. This broadens the scope for investors looking to hedge risks across different financial instruments.

This literature review underscores the complex and evolving relationships between global stock markets, particularly during times of crisis and periods of economic integration. While significant cointegration exists between India and major global markets, emerging and smaller markets present a more mixed picture, offering both risks and diversification opportunities. The COVID-19 pandemic and financial crises have shown that market relationships are dynamic, often weakening during periods of turmoil, only to recover as global economies stabilize. Different cointegration techniques provide nuanced insights into these relationships, and further research is needed to fully understand the implications for investors in an increasingly interconnected world.

METHODOLOGY

The data for this study, covering the period from 2008 to 2023, is sourced from reliable financial databases such as Yahoo Finance, and the official stock exchange websites for each respective index. Daily closing prices of the NSE NIFTY, S&P 500, FTSE 100, Hang Seng, and Nikkei 225 indices have been collected to ensure consistency and accuracy in the analysis. These indices represent major global markets across different regions, including India, the United States, the United Kingdom, Hong Kong, and Japan. The chosen period captures significant global economic events, such as the aftermath of the 2008 financial crisis, the Eurozone debt crisis, and the COVID-19 pandemic, providing a comprehensive dataset for examining the long-term relationships and co-movements between these indices. All data has been adjusted for stock splits and dividends to ensure accuracy in price representation.

The selection of NSE NIFTY, S&P 500, FTSE 100, Hang Seng, and Nikkei 225 for this study is driven by their global significance and regional diversity, representing key financial markets across different economic landscapes. NSE NIFTY reflects the Indian stock market, one of the fastest-growing emerging economies. The S&P 500 is a benchmark for the U.S. market, often seen as a global economic indicator due to the size and influence of the U.S. economy. FTSE 100, from the UK, represents one of the largest financial centres in Europe. Hang Seng is selected for its representation of Hong Kong's market, an important gateway to China's economy, while Nikkei 225 offers insights into Japan, a major player in the Asia-Pacific region. Together, these indices offer a comprehensive view of both developed and emerging markets, making them ideal for analysing global stock market integration and co-movements over the 2008-2023 period.

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. These statistics help in understanding the overall distribution and behaviour of each variable over the 2008-2023 period.

Visual Analysis

Visual analysis through charts such as line plots helps identify trends, patterns, and anomalies in the selected indices over time. It provides a clear depiction of movements, volatility, and correlations between variables during the 2008-2023 period.

Pearson's Correlation

Pearson's correlation among the selected variables measures the strength and direction of linear relationships between indices like NSE NIFTY, S&P 500, FTSE 100, Hang Seng, and Nikkei 225. This analysis reveals how closely these variables move together, highlighting potential interdependencies or inverse relationships.

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

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

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

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

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

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

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.

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) and further elaborated by researchers such as Engle and Granger (1987), Engle and Yoo (1987, 1989), Phillips and Ouliaris (1990), and Johansen (1988, 1991, 1995), among others. In this study, Johansen cointegration and Engle and Granger Residual techniques are employed to assess the number of cointegrated equations.

Johansen Cointegration Test

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

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

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

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

$$y_t = \beta_0 + \beta_1 x_t + e_t \text{ ---(5)}$$

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

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

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.

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

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

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

Analysis and Findings

Table 1: Descriptive statistics of five Global Stock Indices for the period from 2008 to 2023

Variable	NSE NIFTY	S&P 500	FTSE 100	HangSeng	NIKKEI 225
N	4400	4400	4400	4400	4400
Mean	9351.5	2352.9	6456.2	23026	18054
Median	8284.5	2087.2	6622.7	22922	17792
Minimum	2524.2	676.53	3512.1	11016	7055
Maximum	21779	4796.6	8014.3	33154	33753

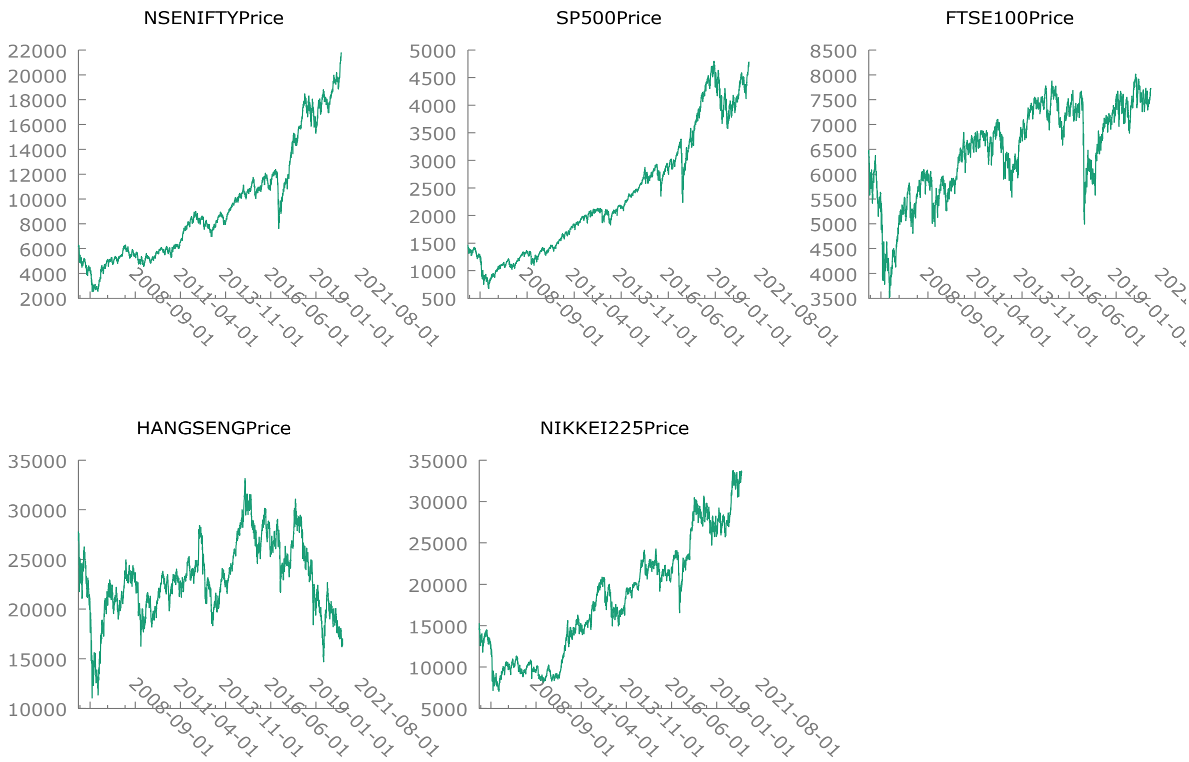
Std. Dev.	4582.9	1112.9	924.63	3753.2	7098.2
C.V.	0.49007	0.47298	0.14322	0.163	0.39317
Skewness	0.80735	0.58947	-0.676	-0.09694	0.28611
Ex. kurtosis	-0.4013	-0.8261	-0.10894	0.08514	-1.0136
IQ range	6001.9	1649.9	1421.8	4845.1	12199

(Source: Author's Calculations)

Table 1 depicts the descriptive statistics of the five international indices (NSE NIFTY, S&P 500, FTSE 100, Hang Seng, and Nikkei 225) provide insights into their central tendencies, dispersion, and distribution patterns over 4400 observations. The mean values indicate that the Hang Seng (HS) and Nikkei 225 indices have the highest average prices (23,026 and 18,054 respectively), reflecting the higher absolute value of these markets. In contrast, the S&P 500 has the lowest mean at 2,352.9, which aligns with its price point structure. The NSE NIFTY has a mean of 9,351.5, reflecting the growth of India's stock market over the years. The median values are slightly lower than the means for all indices, except the FTSE 100, indicating slight positive skewness (right-tailed distributions) for most of the indices.

When analysing volatility, the standard deviation (Std. Dev.) shows that the Nikkei 225 and Hang Seng indices exhibit the most variability (7,098.2 and 3,753.2 respectively), suggesting higher market fluctuations. The coefficient of variation (C.V.), which measures relative variability, indicates that FTSE 100 (C.V. = 0.14322) is the least volatile market relative to its mean, while NSE NIFTY and S&P 500 have slightly higher volatility (C.V. ≈ 0.47-0.49). Skewness values highlight the degree of asymmetry in the distribution of prices, with most indices having a slight positive skew except FTSE 100 and Hang Seng, which show a negative skew (indicating a longer left tail). Excess kurtosis is close to zero for most indices, suggesting that price distributions are relatively normal with mild deviations in tails. Interquartile range (IQR) reveals that Nikkei 225 and Hang Seng have the largest range of values between the 25th and 75th percentiles, indicating wider price dispersion for these markets compared to FTSE 100, which has the narrowest IQR.

Chart 1: Trend of global stock indices daily prices form the 2008 to 2023



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

The chart 1 analysis of the five stock indices — NSE NIFTY, S&P 500, FTSE 100, HANG SENG, and NIKKEI 225 — based on their daily prices from 2008 to 2023, explored from the perspective of cointegration. The NSE NIFTY (Top-left) shows a strong, steady upward trend from 2008 to 2023, reflecting India's economic expansion and capital market growth. When analysing cointegration, we would expect a moderate level of long-term cointegration between NSE NIFTY and developed market indices like the S&P 500 and FTSE 100. While India is a developing market, its increasing integration into the global financial system and exposure to global investor sentiments makes its movement, in the long run, follow similar trends. This would suggest that in times of global market-wide movements (e.g., post-2008 recovery and post-COVID surge), NSE NIFTY could exhibit cointegration with major global indices. However, it may still diverge in the short term due to local economic factors and policy differences.

The S&P 500 (Top-middle), representing the U.S. market, has shown strong performance, particularly post-2010, due to consistent economic growth, low interest rates, and the rise of technology stocks. The S&P 500 is often considered a benchmark for global equity markets, and its long-term price movements have historically shown cointegration with major indices such as FTSE 100 and Nikkei 225. Cointegration is driven by global trade, cross-listed companies, and synchronized monetary policies among developed economies. In the long term, the S&P 500's growth path can be expected to move in tandem with these markets, although short-term divergences may occur due to region-specific economic shocks (like Brexit for FTSE 100 or deflationary pressures in Japan for Nikkei 225).

FTSE 100’s (Top-right) performance has been volatile, showing strong reactions to global and local events like Brexit and changes in global commodity prices. As the index represents a developed economy with significant exposure to commodities and multinational corporations, it has long-term cointegration with indices like the S&P 500 and Nikkei 225, reflecting broader global market trends. However, the degree of cointegration may weaken during periods of region-specific volatility, such as Brexit, which caused a divergence between FTSE 100 and other indices during 2016-2017. Over the long term, FTSE 100 is likely to maintain cointegration with other global indices, especially during periods of synchronized global market movements, such as post-financial crisis recovery and pandemic-era stimuli.

The Hang Seng index (Bottom-left) has shown substantial volatility, especially in response to political and economic uncertainties in Hong Kong and China. Given its regional focus and connection to the Chinese economy, Hang Seng tends to have less cointegration with Western indices like S&P 500 and FTSE 100, as its drivers are more aligned with Chinese economic policies, geopolitical tensions, and regional capital flows. Nonetheless, in the long term, Hang Seng does exhibit some cointegration with global indices due to Hong Kong’s role as a global financial hub. However, the cointegration is weaker compared to indices like FTSE 100 or Nikkei 225, which are more integrated with Western markets. External shocks such as China’s policy changes or trade wars often lead to short-term divergences from other global indices.

The Nikkei 225 (Bottom-right) reflects Japan’s long economic recovery, especially since 2012 under "Abenomics," with significant market intervention by the Bank of Japan. Given Japan's strong trade relations with Western countries and global integration, the Nikkei 225 has long-term cointegration with S&P 500 and FTSE 100. While Japan’s unique economic policies and export-driven structure sometimes led to short-term deviations from global indices, long-term cointegration persists due to Japan’s role in global trade and investment. The post-2020 recovery, seen in most global indices, also supports the view that despite regional policy differences, the Nikkei tends to follow a long-term co-moving path with Western markets. It may, however, show less cointegration with Hang Seng, given the differing economic models and regional factors.

Cointegration analysis reveals that while these five indices may experience short-term divergences due to regional factors, they tend to move together over the long term, especially during global economic cycles. The degree of cointegration varies, with developed markets like S&P 500, FTSE 100, and Nikkei 225 showing stronger long-term relationships, while Hang Seng has weaker cointegration due to its regional focus. NSE NIFTY, as an emerging market index, shows growing cointegration with global indices, reflecting India's increasing integration into global financial systems.

Table 2: Correlation matrix between five global stock indices

Index	NSE NIFTY	S&P 500	FTSE 100	Hang Seng	NIKKEI 225
NSE NIFTY	1	0.9714*	0.7107*	0.2499*	0.9533*
S&P 500	0.9714*	1	0.7468*	0.2995*	0.9506*
FTSE 100	0.7107*	0.7468*	1	0.5354*	0.7612*
Hang Seng	0.2499*	0.2995*	0.5354*	1	0.3899*
NIKKEI 225	0.9533*	0.9506*	0.7612*	0.3899*	1

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

The correlation matrix (Table 2) highlights strong relationships between the five global indices, particularly among the NSE NIFTY, S&P 500, and Nikkei 225 indices. The NSE NIFTY shows a very high positive correlation with the S&P 500 (0.9714) and Nikkei 225

(0.9533), indicating that these markets tend to move in the same direction over time, likely due to globalization and synchronized financial trends. The strong correlation between NSE NIFTY and S&P 500 reflects India's integration into global markets, with both indices responding similarly to international economic factors like liquidity, investor sentiment, and macroeconomic conditions. Meanwhile, Nikkei 225 also has a high correlation with the S&P 500 (0.9506), reflecting the alignment between the Japanese and U.S. markets, possibly driven by trade ties, export-reliant economies, and monetary policies.

The correlation between the FTSE 100 and other indices is moderately strong, particularly with the S&P 500 (0.7468) and Nikkei 225 (0.7612). However, it has a weaker correlation with NSE NIFTY (0.7107), which may reflect the differences in economic sectors (such as FTSE's reliance on commodities and energy) and region-specific factors like Brexit. The Hang Seng index has the lowest correlations across the board, especially with NSE NIFTY (0.2499) and S&P 500 (0.2995), suggesting that the Hong Kong market moves more independently due to its strong ties to China and the region's unique political and economic dynamics. This lower correlation points to diversification benefits when investing in Hang Seng relative to the other indices. However, Hang Seng's higher correlation with FTSE 100 (0.5354) may be explained by shared influences from global commodity prices and multinational corporations.

Unit Root Test

Table 3: Unit root test constant with trend of global stock indices

Global Indices	At Level				First difference			
	ADF	*p-value*	*KPSS*	*p-value*	*ADF*	*p-value*	*KPSS*	*p-value*
NSE NIFTY	-1.7978	0.7061	5.3730	<0.01	-25.5485*	0.0000	0.0344	>0.10
S&P 500	-2.8213	0.1894	4.6994	<0.01	-13.1910*	0.0000	0.0272	>0.10
FTSE100	-1.7287	0.4167	2.2673	<0.01	-14.2135*	0.0000	0.0322	>0.10
HANGSENG	-2.7131	0.2311	2.9994	<0.01	-63.8155*	0.0000	0.0818	>0.10
NIKKEI 225	0.0017	0.9577	2.2328	<0.01	-36.7669*	0.0000	0.0428	>0.10

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

The unit root test table 3 provides insights into the stationarity of major global stock indices, including NSE NIFTY, S&P 500, FTSE 100, HANGSENG, and NIKKEI 225. At the level, the Augmented Dickey-Fuller (ADF) test results show that none of the indices are stationary, as all p-values are above 0.05. For example, NSE NIFTY has an ADF statistic of -1.7978 with a p-value of 0.7061, while NIKKEI 225 has an even higher p-value of 0.9577, indicating a strong presence of a unit root in the level series. The KPSS test further confirms non-stationarity in all indices, as the p-values for each index are less than 0.01, suggesting that they are non-stationary at levels and follow a random walk.

When looking at the first differences, all indices become stationary, as indicated by the highly significant ADF test results. For example, NSE NIFTY has an ADF statistic of -25.5485, and NIKKEI 225 has a value of -36.7669, both with p-values of 0.0000, which strongly reject the null hypothesis of a unit root. The KPSS test results also support these findings, as the p-values for all indices are greater than 0.10, further confirming stationarity in the first-differenced data. These results suggest that although the global stock indices are non-stationary at levels, they become stationary after differencing, making them suitable for time series modelling techniques like cointegration analysis or vector autoregression (VAR) at their first differences.

Johansen Cointegration Test

Table 4: Johansen Cointegration test (Lag order 5) of five global stock indices

Rank	Eigenvalue	Trace test	p-value	Lmax test	p-value
0	0.0094863	97.109*	[0.0000]	37.288*	[0.0152]
1	0.0073123	59.821*	[0.0021]	28.711*	[0.0323]
2	0.0057505	31.110*	[0.0347]	22.561*	[0.0291]
3	0.0015872	8.5492	[0.4158]	6.2139	[0.5927]
4	0.0005967	2.3353	[0.1265]	2.3353	[0.1265]

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

The Johansen cointegration test results (Table 4) reveal that there are up to three cointegrating vectors among the five global indices (NSE NIFTY, S&P 500, FTSE 100, Hang Seng, and Nikkei 225). The significant results for the Trace and Lmax tests for rank 0, 1, and 2 indicate that at least three long-term equilibrium relationships exist between these indices. This suggests that despite short-term fluctuations, these indices move together over time, driven by global economic trends and investor sentiment. The high significance at these ranks reflects the global interconnections in financial markets, where economic factors such as interest rates, monetary policies, and global trade can influence the behaviour of these indices in a similar way. At rank 3, the p-values for both the Trace and Lmax tests are not significant, meaning we cannot reject the null hypothesis that only three cointegrating vectors exist. This implies that beyond the third cointegrating relationship, there are no additional long-term equilibrium links. Therefore, three of the indices share strong long-term movement patterns, while the other two indices might be less integrated or more influenced by regional factors, such as local economic conditions or policy changes, which may cause them to deviate in the short term but still maintain some connection to the global financial system.

Engle-Granger (EG) Cointegration Test

Table 5: Cointegration Regression of Five Global Stock Indices (NSE Nifty Dependent)

Variable	*Coefficient*	*Std. Error*	*t-ratio*	*p-value*	*F Stat*	*R Square*	*Adj R Square*
Constant	1557.08*	128.036	12.16	0.0000	23330* (0.0000)	0.9597	0.9597
S&P 500	2.63617*	0.04687	56.23	0.0000			
FTSE100	−0.1028*	0.02757	−3.73	0.0002			
HANGSENG	−0.1050*	0.00491	−21.4	0.0000			
NIKKEI 225	0.26669*	0.00713	37.40	0.0000			

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

The cointegration regression results, with NSE Nifty as the dependent variable, demonstrate a strong relationship between the Indian stock market and the other four international indices (S&P 500, FTSE 100, Hang Seng, and Nikkei 225). The R-squared value of 0.9597 indicates that approximately 96% of the variance in NSE Nifty's prices can be explained by the movements in the other four indices, highlighting a significant long-term cointegrating relationship. The F-statistic (23330, p-value = 0.0000) confirms the overall significance of the model, suggesting that the independent variables (S&P 500, FTSE 100, Hang Seng, and Nikkei 225) together have a strong impact on NSE Nifty.

Looking at individual coefficients, the S&P 500 has the largest positive impact on NSE Nifty, with a coefficient of 2.63617, meaning that a unit increase in S&P 500 prices is associated with a significant rise in NSE Nifty. Nikkei 225 also shows a positive relationship, albeit weaker, with a coefficient of 0.26669. On the other hand, both FTSE 100 and Hang Seng show significant negative relationships with NSE Nifty, with coefficients of -0.1028 and -0.1050, respectively. These negative coefficients suggest that when these markets rise, NSE Nifty tends to move in the opposite direction to some extent, possibly reflecting the impact of regional economic factors or differing market dynamics. All coefficients are statistically significant, with extremely low p-values (0.0000–0.0002), reinforcing the robustness of the relationships identified in the cointegration analysis.

Table 6: Engle-Granger (EG) cointegration test with constant (ADF) of Global Stock Indices.

Variable	**Estimated Value (a-1)**	**ADF Test Static**	**p Value**
NSE NIFTY	0.000446648	1.19362	0.9982
S&P 500	0.000198673	0.45351	0.9851
FTSE100	-0.00242236	-2.0332	0.2726
HANGSENG	-0.00340844	-2.4693	0.1231
NIKKEI 225	0.000000000	0.02927	0.9601
Residuals Cointegration	-0.01156620	-4.4409*	0.0466

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

The Engle-Granger (EG) cointegration test, as shown in the table 6, applies the Augmented Dickey-Fuller (ADF) unit root test to assess whether individual stock indices, as well as the residuals from the cointegration regression, are stationary. The ADF test statistic and p-values for the individual indices (NSE NIFTY, S&P 500, FTSE 100, Hang Seng, and Nikkei 225) suggest that none of the indices are stationary at their levels. For all indices, the ADF test statistic is quite small (far from the critical values), and the p-

values are all well above the conventional significance levels (p > 0.05). This indicates the presence of a unit root, meaning that the individual indices follow a random walk, which is expected for financial time series data. For instance, the NSE NIFTY has a p-value of 0.9982, and S&P 500 has a p-value of 0.9851, both suggesting non-stationarity. Similarly, Hang Seng and FTSE 100 show negative ADF test statistics but are not significant either.
However, the residuals from the cointegration equation are key in the EG cointegration test. The ADF test statistic for the residuals is -4.4409, and the p-value of 0.0466 is significant at the 5% level, indicating that the residuals are stationary. This confirms the existence of a cointegrating relationship among the indices. Despite the individual series being non-stationary, the stationary residuals suggest that these indices move together in the long run, supporting the presence of cointegration. Therefore, while the stock indices exhibit short-term fluctuations and random walks, they maintain a long-term equilibrium relationship, meaning any deviations from this equilibrium will eventually correct over time. This is consistent with the earlier cointegration results from the Johansen test.

Vector Error Correction Model

Table 7: Error Correction Terms (ECT) of Global Stock Indices

Index	***Coefficient***	***Std. Error***	***t-ratio***	***p-value***
ΔNSE NIFTY	−0.00255706	0.0014616	−1.750	0.0803
ΔS&P 500	0.00895347	0.0014107	6.347	0.0001*
ΔFTSE 100	0.00282521	0.0012546	2.252	0.0244*
ΔHANG SENG	0.00273319	0.001684	1.623	0.1047
ΔNIKKEI 225	0.00152894	0.0016116	0.9487	0.3428

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

The table 7 presents the Error Correction Terms (ECT) for a Vector Error Correction Model (VECM) that analyses the relationship between NSE NIFTY and other global stock indices (S&P 500, FTSE 100, HANGSENG, and NIKKEI 225). The error correction term for NSE NIFTY has a negative coefficient (-0.00255706) and a marginally insignificant p-value (0.0803), indicating that while there is a tendency for NSE NIFTY to correct towards long-term equilibrium, the adjustment is relatively weak and not statistically significant at the 5% level. This suggests that NSE NIFTY may not strongly adjust for short-term deviations from its long-term trend in response to the global stock indices within the studied period. On the other hand, the S&P 500 and FTSE 100 show significant error correction terms, with p-values of 0.0001 and 0.0244, respectively, indicating that both indices exhibit strong and statistically significant adjustments toward their long-run equilibrium. The positive coefficients for both indices suggest that deviations from the equilibrium are corrected over time, and these indices may play a leading role in driving the dynamics of the NSE NIFTY and potentially other global indices.
For the HANGSENG and NIKKEI 225 indices, their error correction terms are not statistically significant, with p-values of 0.1047 and 0.3428, respectively. This implies that these indices do not exhibit strong adjustment mechanisms toward equilibrium in the short term. The lack of significance for these indices may indicate weaker linkages or slower adjustment processes in relation to deviations from their long-run equilibrium compared to the S&P 500 and FTSE 100. Overall, the model indicates that the S&P 500 and FTSE 100 have a significant role in the global financial system's adjustment mechanisms, while the NSE NIFTY exhibits a weaker tendency toward long-term equilibrium correction.

CONCLUSION

The analysis of the correlation matrix, cointegration tests, and Vector Error Correction Model (VECM) underscores the significant interconnectedness of global stock markets, particularly between NSE NIFTY, S&P 500, and Nikkei 225. The strong positive correlations among these indices, especially the very high correlation between NSE NIFTY and S&P 500 (0.9714), reflect the growing synchronization of financial markets due to globalization, shared economic factors, and investor sentiment. The Johansen cointegration test further confirms the presence of at least three long-term equilibrium relationships among the five global indices, suggesting that despite short-term fluctuations, these markets tend to move together over time in response to global macroeconomic trends. The existence of cointegrating vectors signifies that markets like NSE NIFTY, S&P 500, and Nikkei 225 are not only correlated in the short term but are also bound by long-term relationships that align their movements in the global financial system.
The VECM results highlight that both S&P 500 and FTSE 100 exhibit significant error correction mechanisms, meaning these indices strongly adjust toward their long-term equilibrium after short-term deviations. This suggests that these indices play a leading role

in shaping the global stock market dynamics and have a significant influence on the NSE NIFTY. In contrast, the NSE NIFTY itself shows a weaker, statistically insignificant adjustment toward long-term equilibrium, which may indicate that it is more reactive to changes in other global markets, particularly the S&P 500, rather than driving global trends on its own. The relatively weaker linkages for the HANGSENG and NIKKEI 225 indices in the VECM suggest that these markets, while still globally connected, may be influenced by regional or country-specific factors that limit their immediate alignment with global trends.

Finally, the cointegration regression results emphasize the substantial impact that global indices, especially the S&P 500, have on NSE NIFTY, with the model explaining 96% of the variance in NSE NIFTY prices. The positive relationship between S&P 500 and NSE NIFTY, alongside the more modest influence of Nikkei 225, indicates that U.S. and Japanese markets play a crucial role in shaping the Indian stock market's long-term movements. The negative coefficients for FTSE 100 and Hang Seng suggest potential counter-cyclical movements between these indices and NSE NIFTY, possibly driven by differing regional factors or economic sectors. In conclusion, while the NSE NIFTY is closely tied to global financial markets, particularly the U.S. and Japanese markets, it remains responsive to unique local and international economic conditions, as evidenced by the mixed short- and long-term dynamics highlighted in the VECM and cointegration tests.

Scope for Further Research

Future studies could deepen the understanding of these dynamics by incorporating additional macroeconomic variables such as inflation, interest rates, and political risks. Exploring how different phases of economic cycles or financial crises affect these relationships could provide further insights into market behaviour. Additionally, employing more advanced econometric models like time-varying cointegration or machine learning approaches may help capture evolving patterns in global stock markets, enhancing predictive capabilities for investors and policymakers alike. Including other emerging market indices and commodities in the analysis could also yield a broader perspective on global financial interdependencies.

REFERENCES

1) Abdalla, I. S. A., & Murinde, V. (1997). Exchange rate and stock price interactions in emerging financial markets: Evidence on India, Korea, Pakistan and the Philippines. *Applied Financial Economics*, *7*(1), 25–35. https://doi.org/10.1080/096031097333826
2) Agmon, T. (1972). the Relations Among Equity Markets: a Study of Share Price Co-Movements in the United States, United Kingdom, Germany and Japan. *The Journal of Finance*, *27*(4), 839–855. https://doi.org/10.1111/j.1540-6261.1972.tb01315.x
3) Batareddy, M., Gopalaswamy, A. K., & Huang, C. H. (2012). The stability of long-run relationships: A study on Asian emerging and developed stock markets (Japan and US). *International Journal of Emerging Markets*, *7*(1), 31–48. https://doi.org/10.1108/17468801211197888.
4) BECKER, K. G., FINNERTY, J. E., & GUPTA, M. (1990). The Intertemporal Relation Between the U.S. and Japanese Stock Markets. *The Journal of Finance*, *45*(4), 1297–1306. https://doi.org/10.1111/j.1540-6261.1990.tb02438.x.
5) Bhardwaj, N., Sharma, N., & Mavi, A. K. (2022). Impact of Covid-19 on Long Run and Short Run Financial Integration Among Emerging Asian Stock Markets. *Business, Management and Economics Engineering*, *20*(2), 189–206. https://doi.org/10.3846/bmee.2022.16344.
6) Chow, S.-C., Chui, D., Cheng, A., & Wong, W.-K. (2018). The Integration of the Chinese Stock Markets Following the Shanghai, Hong Kong Stock Connect: Evidence from Cointegration, Linear, and Nonlinear Causality Analysis. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3126375.
7) Das, A., & Gupta, A. (2022). Comovement of stock markets after the first COVID wave: a study into five most affected countries. *IIM Ranchi Journal of Management Studies*, *1*(1), 69–81. https://doi.org/10.1108/irjms-07-2021-0055.
8) Deo, M., & Arun Prakash, P. (2017). a Study on Integration of Stock Markets: Empirical Evidence From National Stock Exchange and Major Global Stock Markets. *ICTACT Journal on Management Studies*, *03*(02), 479–485. https://doi.org/10.21917/ijms.2017.0065.
9) Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association, 74 (366a), 427–431.
10) Engle and Granger (1987). Co-Integration and Error Correction: Representation, Estimation, and Testing. *Econometrica, 55(2),* 251-276. https://doi.org/10.2307/1913236.
11) Engle and Yoo (1987). Forecasting and testing in co-integrated systems. *Journal of Econometrics, 35(1),* 143-159, https://doi.org/10.1016/0304-4076(87)90085-6.
12) Füss, R., & Herrmann, F. (2005). *Long-Term Interdependence between Hedge Fund Strategy and Stock Market Indices*. *31*(12), 29–45.

13) Ghulam, Y. A., & Joo, B. A. (2024). Analysing downside risk of BRICS stock indices: insights from value at risk and time series econometrics. *Journal of Financial Economic Policy*. https://doi.org/10.1108/JFEP-01-2024-0022.
14) Granger (1991). Some properties of time series data and their use in econometric model specification. *Journal of Econometrics*, *16(1),* 121-130, https://doi.org/10.1016/0304-4076(81)90079-8.
15) HILLIARD, J. E. (1979). The Relationship Between Equity Indices on World Exchanges. *The Journal of Finance*, *34*(1), 103–114. https://doi.org/10.1111/j.1540-6261.1979.tb02074.x.
16) Johansen,S.(1988). Statistical Analysis of Cointegration Vectors,*Journal of Economic Dynamics,and Control,12(2–3),*231–254.
17) Johansen, S. (1991). Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models, *Econometrica, 59(6),*1551–1580.
18) Johansen, S. (1995). Likelihood-Based Inference in Cointegrated Vector Autoregressive Models (New York: Oxford University Press).
19) Kwiatkowski, D., P. Phillips, P. Schmidt, & Y. Shin (1992). Testing the null hypothesis of stationarity against the alternative of a unit root. *Journal of Econometrics, 54,* 159-178.
20) Lee, H. S. (2004). International transmission of stock market movements: A wavelet analysis. *Applied Economics Letters*, *11*(3), 197–201. https://doi.org/10.1080/1350485042000203850.
21) Marisetty, N. (2021). Indian Index Correlation and Integration with the International Indexes. *SSRN Electronic Journal*, *6*(7), 1–8. https://doi.org/10.2139/ssrn.3142038.
22) Menon, N. R., Subha, M. V., & Sagaran, S. (2009). Cointegration of Indian stock markets with other leading stock markets. *Studies in Economics and Finance*, *26*(2), 87–94. https://doi.org/10.1108/10867370910963028.
23) Nath, G. C., & Verma, S. (2003). Study of Common Stochastic Trend and Co-Integration in the Emerging Markets A Case Study of India, Singapore, and Taiwan. *NSE Research Paper*, *June*, 1–24.
24) Özdemir, L. (2020). Testing for Asymmetric Causality Between Developed and Emerging Markets. *Uncertainty and Challenges in Contemporary Economic Behaviour*, 145–158. https://doi.org/10.1108/978-1-80043-095-220201012.
25) Papavassiliou, V. G. (2014). Equity market integration: The new emerging economy of Montenegro. *Review of Accounting and Finance*, *13*(3), 291–306. https://doi.org/10.1108/RAF-05-2013-0073.
26) Phillips, A. P. C. B., & Ouliaris, S. (1990). Asymptotic Properties of Residual Based Tests for Cointegration. *Econometrica , 58(1),* 165-193. http://www.jstor.org/stable/2938339.
27) Pojanavatee, S. (2014). Cointegration and causality analysis of dynamic linkage between stock market and equity mutual funds in Australia. *Cogent Economics and Finance*, *2*(1). https://doi.org/10.1080/23322039.2014.918855.
28) Prashanth Kumar G., & Marisetty, N. (2023). Dynamic Interdependence: Analysing BSE SENSEX and its Relationship with Global Stock Indices from 2018 to 2022. *Journal of Economics, Management and Trade*, *29*(10), 202–214. https://doi.org/10.9734/jemt/2023/v29i101155.
29) Rao, S. V. R., Marisetty, N., Lohith Kumar, B., & Lohith Kumar, & B. (2021). Design of Portfolio using Multivariate Analysis, *Global Journal of Management and Business Research: A Administration and Management*. *21*(12).
30) Subbaiyan, R., & Arul Sulochana, M. Y. (2020). Cointegration Of Indian And European Stock Market: The Research Of Diversification Opportunities. *International Journal of Disaster Recovery and Business Continuity*, *11*(1), 1310–1316. https://doi.org/10.13140/RG.2.2.29199.10401.
31) Thomas, N. M., Kashiramka, S., & Yadav, S. S. (2017). Dynamic linkages among developed, emerging and frontier capital markets of Asia-Pacific region. *Journal of Advances in Management Research*, *14*(3), 332–351. https://doi.org/10.1108/JAMR-10-2016-0088.
32) Tripathi, V., & Sethi, S. (2010). Integration of Indian stock market with major global stock markets. *Asian Journal of Business and Accounting*, *3*(1), 117–134.
33) Valadkhani, A., & Chancharat, S. (2008). Dynamic linkages between Thai and international stock markets. *Journal of Economic Studies*, *35*(5), 425–441. https://doi.org/10.1108/01443580810903572.
34) Verma, R. P., & Rani, P. (2016). Emerging Stock Market Integration in the Post Financial Crises Era: An Empirical Analysis of the Short-term and Long-term Linkages. *Emerging Economy Studies*, *2*(1), 91–109. https://doi.org/10.1177/2394901516628400.
35) Verma, R. (2024). Comovement of stock markets pre- and post-COVID-19 pandemic: a study of Asian markets. *IIM Ranchi Journal of Management Studies*, *3*(1), 25–38. https://doi.org/10.1108/irjms-09-2022-0086