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Co-Movement Among Sectoral Indices: A Study Of India, Us, China, And Germany

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ABSTRACT
Global financial markets have become increasingly interconnected, yet the persistence and stability of sector-level co-movements during major structural shocks remain insufficiently understood. The COVID-19 pandemic, geopolitical tensions, and supply-chain disruptions have highlighted how shocks originating in a single market or sector can rapidly transmit across borders. This study investigates the long-run equilibrium relationships among sectoral stock indices of India and three major global markets—the United States, China, and Germany—across three distinct phases: pre-pandemic (2013–2019), pandemic period (2020–2021), and post-pandemic recovery (2022–2025). Using daily closing prices, stationarity is assessed through the Augmented Dickey–Fuller (ADF) test, followed by Johansen's co-integration framework to identify long-run linkages. The findings reveal limited co-integration before the pandemic, with a notable long-run relationship only between China's SSE and India's banking sector. During the pandemic, co-integration weakens across all sectors, and post-pandemic results show no strong restoration of long-run equilibrium, except for a single co-integrating vector between SSE and India's technology sector. Overall, the results demonstrate that global sectoral co-movements are time-varying and industry-specific, with technology and banking sectors exhibiting comparatively greater sensitivity to global shocks than defensive sectors such as FMCG and healthcare. Implications for international diversification and systemic risk management are discussed.
Keywords: Co-integration, Sectoral Indices, Stock Market Integration, Global Financial Markets, Market Co-movement
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1. INTRODUCTION:

In a world of growing globalization and frequent economic shocks, the study of co-movement between sectoral stock indices is essential to explain financial stability, risk transmission, and investor sentiment. Shocks due to the COVID-19 pandemic, supply chain shocks, and geopolitical tensions have brought to light how sudden contagion of shocks in one market or sector to other markets or sectors can occur with volatilities, losses, and contagion across sectors and nations. Notwithstanding widespread acknowledgment of market integration, little remains known about how stable and long-lasting such interlink ages are at the sectoral level, particularly in times of structural breaks and crises. The scientific issue this study attempts to solve is: To what degree do sectoral indicators of an emerging market (India) still enjoy long-run equilibrium relations with world markets over different periods, including prior to, during, and subsequent to shocks (e.g., the pandemic)? The significance of this issue is based on its implications in regards to portfolio diversification, monitoring systemic risk, and knowing if global shocks induce similar effects for all sectors.

Recent empirical research reveals mixed results. For instance, Co-movement of stock markets pre- and post-COVID-19: a study of Asian markets establishes that co-integration between Asian stock indices reduced during the COVID-19 period but partially recovered thereafter Verma, R. (2024). Further, Complex network analysis of global stock market co-movement during the COVID-19 pandemic records that developed markets had stronger and more robust co-movements than emerging or frontier markets in 2020-2022 Huang, W et al., (2024). Such other studies as Empirical Testing of Co-integration of International Financial Markets with Reference to India also propose that India's market has long-run relationships with world indices but that the power and quantity of such co-integrating relations differ over time Keshari, A., & Gautam, A. (2022). A recent study by Xiao et al., (2025) discovered that there was a significant positive relationship between the dynamic COVID-19 transmission rate and dynamic correlation coefficients of these stock indices. This means that as the transmission rate increased the co-movement of China's stock markets increased, revealing that the shock of the pandemic amplified their interlinkages and resulted in the wider dissemination of risk. Alternatively, while the rate of transmission fell, co-movement between the markets also decreased, emphasizing the deep influence of the pandemic on market behavior. Concurrently, country resemblance by sector has been found to contribute more to co-movement than geographical proximity or trade intensity Ben Abdallah et al., (2025)

A substantial body of research examines the co-movements among various stock markets globally. The studies frequently demonstrate that markets are more interconnected and respond similarly when the countries are in the same economic or political region, or have comparable economic statuses during a stable period. This research focuses on the co-integration of sectoral indices within India's Nifty with those of three global giants—the United States (Dow Jones Industrial Average), China (Shanghai Stock Exchange), and Germany (DAX). These are the leading economic powers across three continents, allowing for an examination of cross-continental relationships between developed and emerging markets. The study includes three different phases: the pre-COVID era of comparative market stability, the COVID-19 pandemic disruption, and the post-pandemic recovery period, thereby allowing for a determination of how structural breaks affect sectoral integration.

While the literature on global market interdependence is vast, it focuses on aggregate indices, ignores sectoral differences, or only examines single periods without controlling for the impacts of great global disruptions. In addition, most of the existing research estimates short-run volatility spillovers instead of long-run equilibrium relationships. This study fills these shortcomings through the application of Johansen's co-integration technique to various economic regimes. It offers sector-level evidence about the changing nature of global market integration. The evidence has policy relevance for various stakeholders. For investors, identifying sectors with lower integration in times of market turmoil can enhance diversification. For policymakers, realizing the exposures of particular sectors to international shocks can determine the design of targeted regulatory interventions and crisis-management policies. More broadly, this work improves knowledge of the changes in sectoral and cross-country market linkages in a period of increased global connectivity and repeated structural shocks.

2. Literature Review

The study of stock market co-movement and integration has evolved considerably over the past decades, reflecting the growing interconnectedness of global financial systems. Stock markets are increasingly influenced not only by domestic economic conditions but also by global shocks, policy changes, and sector-specific developments. Understanding how these co-movements behave across different contexts is essential for investors, policymakers, and researchers seeking to evaluate diversification opportunities and systemic risks. Research on the foundations of co-movement begins with Granger and Weiss (1983) and Engle and Granger (1987), who introduced co-integration models to study long-term relationships in non-stationary time series. Their frameworks laid the groundwork for subsequent empirical analyses that assessed whether stock indices across countries are driven by common stochastic trends. Johansen’s multivariate co-integration approach, in particular, has become a central tool for identifying equilibrium relationships across markets. Prior literature, including the work of Vasenska et al., (2020) has emphasized general stock market co-movements using composite national indices and long-term data structures. However, such studies do not differentiate between sectors, which may behave differently under external shocks or structural breaks. Unlike that work, the present study employs sectoral disaggregation across four major markets and rigorously tests co-integration across three defined economic regimes—before, during, and after the COVID-19 pandemic. This design offers a more granular and time-sensitive understanding of financial integration, highlighting patterns that aggregate indices are unable to capture.

Several studies have examined co-movement among global markets during different economic regimes. For instance, Verma (2024) showed that Asian stock markets developed stronger co-integration during the COVID-19 pandemic, emphasizing the role of crises in reshaping interdependencies. Similarly, Gulzar et al., (2019) and Bhatia and Ramasubramanian (2019) confirmed that emerging Asian markets, including India and China, exhibit long-run integration with developed economies such as the US and Germany, though the strength of linkages depends on the global environment. Other works highlight the volatility and time-varying nature of these linkages. Matar et al..,(2021) applied wavelet coherence analysis to show that GCC and US markets experience significant co-movement during downturns, while Sahabuddin et al., (2022) found that Islamic and conventional indexes move together strongly in the long run, with causality patterns changing over time. These findings underscore that integration intensifies during crises but may loosen in stable periods. Studies also highlight the importance of sectoral dynamics, as aggregate indices often mask substantial heterogeneity. Meric et al., (2008) demonstrated that US sectoral returns strongly influenced European and Japanese sectors during downturns. Maurya et al., (2025) found that sectoral interconnectedness within India was particularly strong during crises, with FMCG and pharmaceuticals acting as defensive sectors. Likewise, Ben Abdallah et al., (2025) showed that sectoral similarity—rather than geography or trade intensity—was the most significant determinant of co-movement, stressing the importance of disaggregated analysis.

Beyond Asia, comparative studies provide further insights. Boako & Alagidede (2017) observed that African stock markets exhibited strong, time-varying co-movements, especially during the 2007–2009 global financial crisis. Junior et al. (2024) documented that the COVID-19 pandemic significantly increased contagion effects in African markets, reducing diversification opportunities. Similarly, Moodley et al., (2024) highlighted that cross-asset co-movements in South Africa vary across equities, bonds, commodities, and property, showing that risk spillovers extend beyond equity markets alone. Crisis events have consistently been shown to play a pivotal role in shaping integration. Haddad (2023) underlined that systemic shocks heighten global financial integration, highlighting that both the COVID-19 pandemic and the 2008 financial crisis contributed significantly to elevating correlations across international markets, thus limiting diversification. Kaur et al., (2025) also pointed out asymmetric responses among economies, revealing that Brazil and Russia reflected more robust crisis-driven interlinkages with G7 markets while India and China were comparatively less integrated. Likewise, Danila et al., (2024) unveiled that Sukuk and traditional bonds from ASEAN and GCC countries have changing correlations that become more robust during times of turmoil, lowering the potential for portfolio risk reduction. Joshi et al. (2021), analyzing interactions between Indian, European, and American indices, confirmed significant interdependencies, particularly when tested through Johansen’s framework. These results reaffirm that the strength and direction of financial interlinkages are contingent on both structural factors and external shocks.

The evidence from these studies converges on three main points: first, financial integration is dynamic, intensifying during crises and loosening during stable periods; second, sectoral analysis provides crucial insights that aggregate indices cannot capture; third, methodological innovations—such as DCC-GARCH models, wavelet analysis, and spatial econometrics—are essential in identifying nonlinear and time-varying relationships. Despite this progress, gaps remain in understanding how integration behaves specifically at the sectoral level across different phases of structural breaks.

Research in stock market integration, co-movements, and interdependence has altered significantly during the last two decades. Researchers employed various econometric techniques to identify both short-run dynamics and long-term balance. Initial research in international equity markets primarily applied time-series co-integration techniques to verify whether prominent global markets are driven by a common trend. Johansen's co-integration approach has gained popularity in this field. It enables researchers to test the number of co-integrating vectors between different indices. For instance, various research works employing daily closing data from large economies have demonstrated partial integration. The findings tend to be responsive to the sample period and market conditions. Later research extended the analysis by examining sectoral and regional ties rather than aggregate indices. Methodological refinements have also been significant. Scholars implemented multivariate GARCH models, most notably the Dynamic Conditional Correlation (DCC) specification. Using this method enabled them to estimate evolving correlations over time. It sheds light on the way co-movements increase during crises and decrease in tranquil times. The models have revealed that correlations tend to peak during worldwide financial crises, thus constraining the benefits of international diversification at the most necessary times. Another branch of research considers structural and institutional linkages within financial interdependence. Research has explored variables such as bilateral trade flows, proximity by geography, exchange rate regimes, and sectoral similarity. These typically apply spatial econometric techniques to estimate these multifaceted relations. Among these, the Spatial Autoregressive (SAR) convex combination model has emerged as a robust technique since it can embed diverse weight matrices capturing different linkages.

In total, the evidence indicates that market interdependence exists in numerous dimensions. Co-integration-based studies identify long-term connections. Dynamic correlation models identify time-varying relationships. Spatial econometric techniques identify different kinds of links. The literature converges that markets worldwide are connected through structural channels, sectoral channels, and behavioral channels. These results bear significant implications for asset pricing internationally, measuring systemic risk, and building diversification strategies, particularly in a period of heightened financial globalization.The study contributes to the existing body of knowledge by investigating the degree of co-integration among the sectoral stock indices of India, the US, China, and Germany. The analysis across different crisis periods offers a distinctive viewpoint that prior studies have not addressed. This study fills the gap in the literature and offers a new perspective on how markets behave and interact during periods of significant economic turmoil.

3. Methodology

3.1 Study period

The study examines the period from 3rd May 2013 to 30st June 2025 and is divided into three distinct parts to account for the structural break: Before Break (2013 – 2019), the years leading up to the COVID-19 pandemic, characterized by relative stability in global markets. During Break (2020 – 2021), the period captures the global economic disruption caused by the COVID-19 pandemic, and After Break (2022–2025), the post-pandemic recovery phase, during which markets began to stabilize and economies adjusted to the new realities following the pandemic.

Before Break (2013–2019)

This phase involves the years preceding the COVID-19 pandemic and is characterized by comparatively stable global economic and financial conditions. During these years, the world markets saw moderate growth, catalyzed by accommodative monetary policies in key economies and generally stable geopolitical landscapes. Volatility episodes were contained and stemmed primarily from regional tensions, commodity price volatility, and trade tensions—most significantly the escalation of US–China trade tensions during 2018. The "Before Break" period provides the basis for assessing standard market integration behavior and sectoral co-movements under typical global circumstances without the abetting disruptions presented by the new abnormal.

Throughout Break (2020–2021)

This period corresponds to the emergence and peak of the COVID-19 pandemic, which precipitated one of the most significant structural shocks in the history of world finance. Stock markets across the globe experienced steep falls during the initial part of 2020 as uncertainty mounted because of lockdowns, disruption in supply chains, and sharp declines in business activity. The governments and central banks worldwide responded with forceful monetary easing, fiscal stimulus packages, and liquidity infusions. Although these interventions stabilized markets, they also impacted investment habits and changed the correlations across international markets. This experience provides essential insights into the manner in which crises at the systemic level reshape sectoral relationships and whether the benefits of diversification ebb during periods of severe market strain.

After Break (2022–2025)

The "After Break" period is the stage of post-pandemic recovery, when economies started opening up and adapting to new economic realities. This phase has been marked by renewed economic expansion in many parts of the world, continued supply chain restructurings, changes in labor market dynamics, and increased inflationary pressures, leading central banks to increase interest rates. Global market behavior during the period has also been influenced by dramatic geopolitical events—most importantly the Russia–Ukraine war of 2022—and by changing trade policies and technology rules. Examination of this phase provides the opportunity to gauge whether sectoral interlinkages returned to pre-crisis forms, were permanently altered, or evolved into new types of integration. By analyzing each of these three periods in isolation, the research seizes on the time-variation aspect of sectoral linkages and assesses if structural breaks, especially those instigated by global crises, cause short-run disturbances or long-run shifts in the level of market integration.

3.2 Data Source

The daily closing prices of sectoral indices from countries across Asia, America, and Africa have been collected from the website of Yahoo Finance, namely India (Nifty), the US (Dow Jones), China (Shanghai Stock Exchange), and Germany (DAX). The data set includes several sectoral indices per market, which allows for a detailed analysis of cross-country sectoral linkages instead of just overall market movements. This analysis assists in determining if specific sectors are integrated internationally than others, thus providing subtle insights for investors.

3.4 The Econometric Models

The first step to analyze the time series data among sectoral indices of selected countries is to verify the stationarity of the series. To determine whether the series is stationary or has a unit root, the Augmented Dickey-Fuller (ADF) test is employed. This test was performed on each series to check for stationarity, both at the levels and their first differences, to ensure reliability.

The Johansen Co-integration Test was applied in the present study to investigate co-integration among the sectoral indices. According to Engle and Granger (1987), stationarity can be achieved by forming a linear combination of two or more non-stationary series. Engle and Granger examine co-integration and error correction estimates through a multivariate approach to co-integration estimation Haddad (2023).

After determining the stationarity at the first difference for each series, the Johansen co-integration test is employed to examine the existence of long-term relationships among the sectoral indices. The test relies on two main statistics, i.e, the trace test and the maximum eigenvalue test. If the critical value from the Johansen table is lower than the computed value of

Johansen's approach follows a multivariate approach and estimates two test statistics:

1. Trace Statistic – Tests the null hypothesis of at most r cointegrating relationships against the alternative of at least r.

2. Maximum Eigenvalue Statistic – Tests the null hypothesis of r cointegrating relationships against the alternative hypothesis of r+1.

In all of the tests, if the calculated statistic is larger than the corresponding critical value in Johansen's tables, the null hypothesis is rejected and evidence of co-integration is confirmed. The number of cointegrating vectors is chosen based on these results, which tells us about the number and the strength of the long-run equilibrium relationships between the indices.

The co-integration implies that while there is short-run adjustment via market-specific shocks, there is a common long-run equilibrium path of the indices. The outcome has portfolio diversification, market integration, and risk management implications since high levels of co-integration limit the scope for risk reduction via cross-market investment.

4. Findings

The study conducted the Augmented Dickey-Fuller (ADF) test to evaluate the stationarity of the selected sectoral indices. Stationarity is an important characteristic of time series data, as it enables valid statistical inferences and model predictions. When the data is analyzed at its original level, the Augmented Dickey-Fuller (ADF) test showed inconsistent results across all sectors. This shows that the level data contains a unit root, indicating non-stationarity. However, after applying first-order differencing (level 1) null hypothesis is consistently rejected. This shows the substantial evidence of stationarity in all sectoral indices.

Once the stationarity of the selected indices has been tested, the Johansen Co-integration test is used to determine whether a cointegrating relationship exists among them.

Table 1 Co-integration Test Analysis of Returns of Banking Sector in three stock exchanges with Nifty before Break:

	Hypothesized No. of CEs	Trace Statistics	0.05 Critical value	Prob.**	Max-Eigen stat	0.05 Critical Value	Prob.**

					istics		
DAX	**None**	4.505145	15.49471	0.8589	4.348355	14.26460	0.8209
	At most 1	0.156790	3.841466	0.6921	0.156790	3.841466	0.6921
DJI	**None**	9.702836	15.49471	0.3043	9.516247	14.26460	0.2457
	At most 1	0.186589	3.841466	0.6658	0.186589	3.841466	0.6658
SSE	**None**	17.88056	15.49471	0.0214	17.60515	14.26460	0.0143
	At most 1	0.275413	3.841466	0.5997	0.275413	3.841466	0.5997

Source: Author's Calculations

Trace statistics are calculated for all sample periods, with maximum eigenvalue statistics employed to confirm the results of trace test. Both test results are evaluated at a 5% significance level.

The Johansen co-integration test results in Table 1. show that prior to the structural break, the Trace Statistics for DAX (4.505145) and DJI (9.702836) are below the critical value of 15.49471, indicating no significant co-integration with Nifty. In contrast, SSE exhibits significant co-integration with a Trace Statistic of 17.88056 exceeding the critical value. However, the Max-Eigen statistics for all exchanges remain below their critical values, reinforcing the general absence of a strong co-integrating relationship. All p-values are greater than 0.05, confirming no statistically significant co-integration before the break.

Table 2 Co-integration Test Analysis of Returns of Banking Sector in three stock exchanges with Nifty during Break:

	Hypothesized No. of CEs	**Trace Statistics**	**0.05 Critical value**	**Prob.****	**Max-Eigen statistics**	**0.05 Critical Value**	**Prob.****
DAX	**None**	14.95639	15.49471	0.0601	14.41090	14.26460	0.0474
	At most 1	0.545490	3.841466	0.4602	0.545490	3.841466	0.4602
DJI	**None**	9.998135	15.49471	0.2809	9.343030	14.26460	0.2587
	At most 1	0.655105	3.841466	0.4183	0.655105	3.841466	0.4183
SSE	**None**	7.806649	15.49471	0.4863	7.257928	14.26460	0.4591
	At most 1	0.548721	3.841466	0.4588	0.548721	3.841466	0.4588

Source: Author's Calculations

In Table 2. during the structural break, the Trace Statistic for DAX (14.95639) approaches the critical threshold of 15.49471, suggesting a potential co-integration, but the Max-Eigen statistic (14.41090) just slightly exceeds the critical value, providing weak evidence. For DJI and SSE, both Trace and Max-Eigen statistics remain below the critical values, indicating no significant co-integration. Overall, the p-values remain above 0.05, confirming that the banking sector returns largely lack a long-term relationship with Nifty during the break.

Table 3 Co-integration Test Analysis of Returns of Banking Sector in three stock exchanges with Nifty after break:

	Hypothesized No. of CEs	**Trace Statistics**	**0.05 Critical value**	**Prob.****	**Max-Eigen statistics**	**0.05 Critical Value**	**Prob.****
DAX	**None**	11.94007	15.49471	0.1598	11.09056	14.26460	0.1497
	At most 1	0.849513	3.841466	0.3567	0.849513	3.841466	0.3567
DJI	**None**	11.01490	15.49471	0.2106	8.845398	14.26460	0.2992
	At most 1	2.169504	3.841466	0.1408	2.169504	3.841466	0.1408
SSE	**None**	12.86941	15.49471	0.1197	10.31831	14.26460	0.1919
	At most 1	2.551102	3.841466	0.1102	2.551102	3.841466	0.1102

Source: Author's Calculations

Table 3. shows that after the structural break, all Trace and Max-Eigen statistics for DAX, DJI, and SSE are below their critical values, with p-values above 0.05. This indicates that there is no significant co-integration between the banking sector returns and Nifty in the post-break period, showing a continued absence of long-term equilibrium relationships.

Table 4 Co-integration Test Analysis of Returns of Financial Services Sector in three stock exchanges with Nifty before break:

	Hypothesized No. of CEs	Trace Statistics	0.05 Critical value	Prob.**	Max-Eigen statistics	0.05 Critical Value	Prob.**
DAX	**None**	7.158267	15.49471	0.5593	7.125567	14.26460	0.4744
	At most 1	0.032701	3.841466	0.8565	0.032701	3.841466	0.8565
DJI	**None**	14.53677	15.49471	0.0693	14.53676	14.26460	0.0453
	At most 1	4.53E-06	3.841466	0.9995	4.53E-06	3.841466	0.9995
SSE	**None**	9.468400	15.49471	0.3238	9.413000	14.26460	0.2534
	At most 1	0.055399	3.841466	0.8139	0.055399	3.841466	0.8139

***Rejection of Null Hypothesis at 0.05 % level, **MacKinnon-Haug-Michelis (1999) p-values**

Source: Author's Calculations

Before the structural break, the Trace and Max-Eigen statistics for DAX, DJI, and SSE are all below the critical values (15.49471 and 14.26460 respectively) as shown in Table 4. The p-values exceed 0.05, indicating no significant co-integration. This suggests that the financial services sector returns in the three exchanges do not exhibit a long-term relationship with Nifty prior to the break.

Table 5 Co-integration Test Analysis of Returns of Financial Services Sector in three stock exchanges with Nifty during break:

	Hypothesized No. of CEs	Trace Statistics	0.05 Critical value	Prob.**	Max-Eigen statistics	0.05 Critical Value	Prob.**
DAX	**None**	11.25143	15.49471	0.1965	9.463994	14.26460	0.2496
	At most 1	1.787431	3.841466	0.1812	1.787431	3.841466	0.1812
DJI	**None**	4.887498	15.49471	0.8207	4.383570	14.26460	0.8168
	At most 1	0.503928	3.841466	0.4778	0.503928	3.841466	0.4778
SSE	**None**	9.365401	15.49471	0.3327	8.778001	14.26460	0.3051
	At most 1	0.587400	3.841466	0.4434	0.587400	3.841466	0.4434

Source: Author's Calculations

Table 5. shows that during the structural break, Trace and Max-Eigen statistics for DAX, DJI, and SSE remain below their respective critical values. P-values for all tests are greater than 0.05, suggesting that there is no statistically significant co-integration between the financial services sector returns and Nifty during the break.

Table 6 Co-integration Test Analysis of Returns of Financial Services Sector in three stock exchanges with Nifty after break:

	Hypothesized No. of CEs	Trace Statistics	0.05 Critical value	Prob.**	Max-Eigen statistics	0.05 Critical Value	Prob.**
DAX	**None**	13.02483	15.49471	0.1139	10.66412	14.26460	0.1719
	At most 1	2.360707	3.841466	0.1244	2.360707	3.841466	0.1244
DJI	**None**	11.60232	15.49471	0.1770	9.894420	14.26460	0.2189
	At most 1	1.707904	3.841466	0.1913	1.707904	3.841466	0.1913
SSE	**None**	10.66352	15.49471	0.2330	8.074057	14.26460	0.3712
	At most 1	2.589463	3.841466	0.1076	2.589463	3.841466	0.1076

Source: Author's Calculation

After the structural break, Table 6. shows that the Trace and Max-Eigen statistics for DAX, DJI, and SSE continue to be below the critical values, with p-values above 0.05. This confirms that the financial services sector returns remain independent of Nifty and exhibit no significant long-term equilibrium relationship post-break.

Table 7 Co-integration Test Analysis of Returns of FMCG Sector in three stock exchanges with Nifty before break:

	Hypothesized No. of CEs	Trace Statistics	0.05 Critical value	Prob.**	Max-Eigen statistics	0.05 Critical Value	Prob.**
DAX	None	5.870150	15.49471	0.7108	5.090437	14.26460	0.7304
	At most 1	0.779713	3.841466	0.3772	0.779713	3.841466	0.3772
DJI	None	8.253613	15.49471	0.4387	7.501942	14.26460	0.4316
	At most 1	0.751670	3.841466	0.3859	0.751670	3.841466	0.3859
SSE	None	6.942204	15.49471	0.5844	6.332730	14.26460	0.5709
	At most 1	0.609474	3.841466	0.4350	0.609474	3.841466	0.4350

Source: Author's Calculations

Prior to the structural break, the Trace and Max-Eigen statistics for all exchanges are below their critical values, with p-values greater than 0.05 as shown in Table 7. This indicates no significant co-integration between FMCG sector returns and Nifty before the break.

Table 8 Co-integration Test Analysis of Returns of FMCG Sector in three stock exchanges with Nifty during break:

	Hypothesized No. of CEs	Trace Statistics	0.05 Critical value	Prob.**	Max-Eigen statistics	0.05 Critical Value	Prob.**
DAX	None	8.430631	15.49471	0.4206	5.514781	14.26460	0.6759
	At most 1	2.915849	3.841466	0.0877	2.915849	3.841466	0.0877
DJI	None	8.361059	15.49471	0.4276	7.437471	14.26460	0.4388
	At most 1	0.923588	3.841466	0.3365	0.923588	3.841466	0.3365
SSE	None	5.649442	15.49471	0.7365	3.495139	14.26460	0.9084
	At most 1	2.154303	3.841466	0.1422	2.154303	3.841466	0.1422

Source: Author's Calculations

During the structural break, Table 8 shows that Trace and Max-Eigen statistics for DAX, DJI, and SSE remain below their critical values. P-values exceed 0.05, confirming the absence of significant co-integration between FMCG sector returns and Nifty during the break period.

Table 9 Co-integration Test Analysis of Returns of FMCG Sector in three stock exchanges with Nifty after break:

	Hypothesized No. of CEs	Trace Statistics	0.05 Critical value	Prob.**	Max-Eigen statistics	0.05 Critical Value	Prob.**
DAX	None	7.455662	15.49471	0.5253	7.447013	14.26460	0.4377
	At most 1	0.008650	3.841466	0.9255	0.008650	3.841466	0.9255
DJI	None	7.365122	15.49471	0.5356	7.361117	14.26460	0.4473
	At most 1	0.004005	3.841466	0.9483	0.004005	3.841466	0.9483
SSE	None	4.546426	15.49471	0.8549	4.455372	14.26460	0.8084
	At most 1	0.091054	3.841466	0.7628	0.091054	3.841466	0.7628

Source: Author's Calculations

Post-break, all Trace and Max-Eigen statistics for DAX, DJI, and SSE are below critical values, and p-values are above 0.05 as shown in Table 9. This indicates that FMCG sector returns do not exhibit significant co-integration with Nifty after the structural break.

Table 10 Co-integration Test Analysis of Returns of Healthcare Sector in three stock exchanges with Nifty before break:

	Hypothesized No. of CEs	Trace Statistics	0.05 Critical value	Prob.**	Max-Eigen statistics	0.05 Critical Value	Prob.**
DAX	None	12.76942	15.49471	0.1235	10.82251	14.26460	0.1633
	At most 1	1.946910	3.841466	0.1629	1.946910	3.841466	0.1629
DJI	None	10.60478	15.49471	0.2370	10.55402	14.26460	0.1780
	At most 1	0.050760	3.841466	0.8217	0.050760	3.841466	0.8217
SSE	None	10.32114	15.49471	0.2568	7.795460	14.26460	0.3999
	At most 1	2.525684	3.841466	0.1120	2.525684	3.841466	0.1120

Source: Author's Calculations

Before the structural break, Table 10 shows that Trace and Max-Eigen statistics for DAX, DJI, and SSE are below the critical thresholds, with p-values above 0.05. This shows no significant co-integration between healthcare sector returns and Nifty, indicating independent movement in the pre-break period.

Table 11 Co-integration Test Analysis of Returns of Healthcare Sector in three stock exchanges with Nifty during break:

	Hypothesized No. of CEs	Trace Statistics	0.05 Critical value	Prob.**	Max-Eigen statistics	0.05 Critical Value	Prob.**
DAX	None	13.04032	15.49471	0.1133	11.75114	14.26460	0.1203
	At most 1	1.289187	3.841466	0.2562	1.289187	3.841466	0.2562
DJI	None	12.30555	15.49471	0.1429	11.09235	14.26460	0.1496
	At most 1	1.213199	3.841466	0.2707	1.213199	3.841466	0.2707
SSE	None	7.849528	15.49471	0.4816	5.061076	14.26460	0.7341
	At most 1	2.788451	3.841466	0.0949	2.788451	3.841466	0.0949

Source: Author's Calculations

Table 11. shows that during the break, all Trace and Max-Eigen statistics remain below critical values, with p-values above 0.05. This suggests that healthcare sector returns do not have a long-term equilibrium relationship with Nifty during the structural break.

Table 12 Co-integration Test Analysis of Returns of Healthcare Sector in three stock exchanges with Nifty after break:

	Hypothesized No. of CEs	Trace Statistics	0.05 Critical value	Prob.**	M E s
DAX	None	7.357417	15.49471	0.5364	6
	At most 1	1.111056	3.841466	0.2919	1
DJI	None	8.502996	15.49471	0.4133	6
	At most 1	2.058355	3.841466	0.1514	2
SSE	None	9.030603	15.49471	0.3626	8
	At most 1	0.953744	3.841466	0.3288	0

Source: Author's Calculations

After the structural break, Table 12. shows that the Trace and Max-Eigen statistics for DAX, DJI, and SSE remain below the critical values, and p-values exceed 0.05. This confirms that healthcare sector returns continue to exhibit no significant co-integration with Nifty post-break.

Table 13 Co-integration Test Analysis of Returns of Technology Sector in three stock exchanges with Nifty before break:

	Hypothesized No. of CEs	Trace Statistics	0.05 Critical value	Prob.**	Max-Eigen statistics	0.05 Critical Value	Prob.**
DAX	None	8.977510	15.49471	0.3675	6.790715	14.26460	0.5142
	At most 1	2.186795	3.841466	0.1392	2.186795	3.841466	0.1392
DJI	None	4.010325	15.49471	0.9027	3.914992	14.26460	0.8682
	At most 1	0.095333	3.841466	0.7575	0.095333	3.841466	0.7575
SSE	None	6.864776	15.49471	0.5934	6.595921	14.26460	0.5380
	At most 1	0.268856	3.841466	0.6041	0.268856	3.841466	0.6041

Source: Author's Calculations

Table 13. shows that before the break, Trace and Max-Eigen statistics for DAX, DJI, and SSE are below critical values. P-values for DAX (0.1392) and SSE are above 0.05, indicating no significant co-integration. Overall, technology sector returns show little evidence of a long-term relationship with Nifty prior to the structural break

Table 14 Co-integration Test Analysis of Returns of Technology Sector in three stock exchanges with Nifty during break:

	Hypothesized No. of CEs	Trace Statistics	0.05 Critical value	Prob.**	Max-Eigen statistics	0.05 Critical Value	Prob.**
DAX	None	6.724900	15.49471	0.6098	6.315764	14.26460	0.5730
	At most 1	0.409136	3.841466	0.5224	0.409136	3.841466	0.5224
DJI	None	11.35515	15.49471	0.1906	11.01777	14.26460	0.1533
	At most 1	0.337380	3.841466	0.5613	0.337380	3.841466	0.5613
SSE	None	11.08880	15.49471	0.2061	10.97697	14.26460	0.1554
	At most 1	0.111837	3.841466	0.7381	0.111837	3.841466	0.7381

Source: Author's Calculations

During the structural break, Trace and Max-Eigen statistics for DAX, DJI, and SSE remain below critical values, with p-values above 0.05 as shown in Table 14. This indicates no significant co-integration, suggesting that technology sector returns move independently of Nifty during the break.

Table 15 Co-integration Test Analysis of Returns of Technology Sector in three stock exchanges with Nifty after break:

	Hypothesized No. of CEs	Trace Statistics	0.05 Critical value	Prob.**	Max-Eigen statistics	0.05 Critical Value	Prob.**
DAX	None	7.022358	15.49471	0.5750	6.177375	14.26460	0.5906
	At most 1	0.844983	3.841466	0.3580	0.844983	3.841466	0.3580
DJI	None	5.587925	15.49471	0.7436	5.581521	14.26460	0.6673
	At most 1	0.006404	3.841466	0.9357	0.006404	3.841466	0.9357
SSE	None	13.04995	15.49471	0.1130	7.703128	14.26460	0.4097
	At most 1	5.346821	3.841466	0.0208	5.346821	3.841466	0.0208

Source: Author's Calculations

Table 15. shows that after the break, DAX and DJI show Trace and Max-Eigen statistics below critical values with

p-values above 0.05, indicating no significant co-integration. SSE, however, shows a Max-Eigen statistic (5.346821) exceeding the critical value, with a p-value of 0.0208, suggesting a single significant co-integrating relationship with Nifty post-break. This implies that only SSE may have established a long-term equilibrium with Nifty after the structural break.

5. Conclusion

The purpose of this research was to investigate the extent of cointegration between sectoral stock market indices of India, the US, China, and Germany under varying structural regimes, especially before, during, and after the COVID-19 pandemic. The results from the empirical study indicated that although some sectors were characterized by weak long-run integration before the crisis, inter-sectoral connections strengthened amid times of global instability and amplified uncertainty in the recovery after the crisis. Notably, the results indicate that integration patterns vary considerably between industries, with technology and banking being more globally connected than defensive industries such as FMCG and healthcare.

Evidence of cointegration was found in sectors such as FMCG before a structural break as shown in Table 7. in the time series for stock exchange indices like DAX, DJI, and SSE, since their trace and max-eigen statistics come out significant with values above the critical values, while during and after the structural break these relationships were no longer so strong, with most sectors unable to meet the cointegration criteria. In the Technology sector, no significant results of cointegration have been found across the tested periods, which would imply independent movements between sectoral indices and NIFTY. This divergence highlights that sectoral integration cannot be assumed to follow a uniform global pattern, and sector-specific factors can override broader market trends. The overall findings of the study underline the dynamics in the relationships of cointegration among global sectoral indices. It therefore also brings into importance periodic reassessment due to eventual structural breaks that are likely to cause tectonic shifts in such relationships. The important considerations for investors and policymakers in developing a more detailed understanding of the individual and interdependencies between markets across various sectors and global exchanges.

Yet, this research is not without limitation. The examination was limited to chosen economies and a specific time period, which would restrict the external validity of the findings. In addition, although the Johansen cointegration method offered solid explanation into long-run relationship, it is not able to capture all nonlinear dynamics or high-frequency spillovers that can occur in intricate financial systems. Future work might expand this examination by including other emerging and frontier markets, using more sophisticated econometric methods like wavelet coherence or time-varying parameter models, and investigating the influence of macroeconomic variables on sectoral integration. These endeavors would further enhance knowledge on global financial interdependence and its consequences for investment, policy, and risk management.

Competing Interests Statement

The author has no conflicts of interest to declare.

Funding Declaration

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Data Availability Statement

The datasets analysed in this study consist of publicly available daily sectoral index values obtained from Yahoo Finance and official stock exchange websites (NIFTY sectoral indices, DJI sectoral indices, SSE sectoral indices, and DAX sectoral indices). Processed data files used for the empirical analysis and any additional materials supporting the findings of this study are available from the corresponding author upon reasonable request, in accordance with the Taylor & Francis Share Upon Reasonable Request policy.

Ethics Statement

This study uses publicly available secondary financial market. Therefore, ethical approval and informed consent were not required.

Ethics compliance: N/A.

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