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Co-Integration and Causality in Indian Market Indices: Pre-COVID vs. COVID-19 Perspectives

J. Sahaya Shabu*, J. Divya Merry Malar**

Abstract. *This study investigates the co-integration and Granger causality relationships among key indices in the Indian stock market, focusing on small-cap, mid-cap, large-cap stocks, and the Nifty indices during the pre-COVID and COVID-19 periods. Utilizing the Johansen Co-integration Test, the research examines stable long-term equilibrium relationships among these indices. Findings reveal robust co-integration between the Nifty 50 index and NIFTY100, NIFMDCP100, and NIFSMCP100 during the pre-COVID era, indicating significant interdependence. However, indices not involving the Nifty 50 showed less consistent co-integration. During the COVID-19 pandemic, while some relationships remained stable, others weakened, highlighting the pandemic's disruptive impact. Granger causality tests further elucidate causal influences among these indices, emphasizing shifts in influence dynamics, particularly the pivotal role of the NIFTY100 index. These insights are crucial for stakeholders in finance and policymaking, offering valuable implications for portfolio management, risk mitigation, and policy formulation amidst evolving market conditions.*

Keywords *Indian Stock Market, Co-Integration, Granger Causality, COVID-19, Econometric Analysis*

INTRODUCTION

Financial markets are complex systems influenced by a multitude of factors, including economic conditions, investor behavior, policy changes, and global events. Understanding the interrelationships among different market segments is crucial for investors, policymakers, and analysts seeking to navigate market dynamics effectively.

The Indian stock market, characterized by its diverse range of market indices and sectors, reflects the complexities of a rapidly growing economy. Over the years, the market has witnessed significant structural changes and volatility, influenced by both domestic and global economic factors (Rajput & Jain, 2012). The behavior of market indices, such as the Nifty 50, NIFTY100, NIFMDCP100, and NIFSMCP100, often reveals underlying patterns of co-movement and causal relationships under varying economic conditions.

Historically, studies on market interrelationships have utilized econometric tools like co-integration and Granger causality to explore the persistence of long-term equilibrium relationships and the directionality of causal influences among financial assets (Engle & Granger, 1987; Johansen, 1995; Cheung & Ng, 1996). These methods provide insights into how different market segments interact over time, contributing to our understanding of market efficiency and risk management strategies.

The theoretical foundation of this study relies on two fundamental econometric techniques. The Johansen Co-integration Test, developed by Søren Johansen, identifies co-integration among multiple time series variables, indicating a stable long-term relationship despite short-term fluctuations (Johansen, 1995). This analysis in financial markets helps determine whether specific market indices move together over extended periods, despite temporary disruptions caused by market shocks or fluctuations. The Granger Causality Test, named after Clive Granger, assesses whether past values of one time series can predict future values of another series beyond its own past values (Granger, 1969). It measures the direction and strength of causal relationships between variables, providing insights into how changes in one market segment may impact others over time (Cheung & Ng, 1996). In financial markets, Granger causality elucidates the transmission of information, shocks, or trends among different asset classes or indices, enhancing understanding of market dynamics and informing management strategies.

This study holds significant implications for various stakeholders. For investors, a deeper understanding of co-integration and causal relationships among market indices enables the construction of diversified portfolios that effectively balance risk and return. Such insights facilitate strategic asset allocation strategies aimed at mitigating market volatility and optimizing investment outcomes. Policymakers benefit from accurate assessments of market

* Assistant Professor, Xavier Institute of Business Administration, St. Xavier's College (Autonomous), Palayamkottai, Tirunelveli, Tamil Nadu, India. Email: jjshabu@gmail.com
** Assistant Professor, Department of Commerce, Holy Cross College (Autonomous), Nagercoil, Affiliated to Manonmaniam Sundaranar University, Tirunelveli, Tamil Nadu, India. Email: divyanvin@gmail.com

interdependencies, crucial for crafting resilient regulatory frameworks and targeted economic interventions. By leveraging the study's insights, policymakers can foster market stability and enhance investor confidence through well-informed policy decisions. Furthermore, for analysts and researchers, this study contributes to advancing knowledge in financial market dynamics within emerging economies. Through rigorous econometric analyses, it provides empirical evidence on how different segments of the Indian stock market interact under varying economic conditions, thereby enriching scholarly discourse and expanding the collective understanding of market behavior.

This study aims to explore how different market cap segments of the Indian stock market are connected using advanced math and economics techniques. By looking at co-integration and Granger causality in different market sections, it hopes to give clear advice that can help people make better decisions and learn more about how financial markets work in different economic situations.

LITERATURE REVIEW

The field of econometrics has been significantly enriched by seminal studies and empirical works that have advanced our understanding of economic dynamics, financial market interactions, and the methodologies used to analyze them. Engle and Granger (1987) introduced co-integration and error correction models (ECMs) as powerful tools for modeling non-stationary time series data and capturing long-term equilibrium relationships among variables. Their Error Correction Model (ECM) framework addresses the challenge of modeling economic and financial data with trends or unit roots, providing insights into both short-term dynamics and long-term relationships.

Building on Engle and Granger's foundation, Johansen (1988) extended co-integration analysis by developing statistical methods to identify and estimate multiple co-integration relationships among time series variables. This framework, known as the Johansen procedure, allows for the estimation of co-integrating vectors and provides tests to determine the number of stable long-term relationships present in a set of variables. Cheung and Ng (1996) further expanded the application of Granger causality tests by introducing a causality-in-variance test, which assesses whether past information in one financial variable can predict the variance of another, complementing traditional mean-based Granger causality tests.

Empirical studies by Diebold and Yilmaz (2009), Baele et al. (2004), and Geweke and Porter-Hudak (1983) have focused on measuring financial market integration, return spillovers, and modeling long memory in time series data, respectively. Diebold and Yilmaz's framework quantifies return and volatility spillovers across global equity markets, highlighting the interconnectedness of financial markets and the propagation of market disturbances. Baele et al.'s work examines the degree of financial integration within Europe, using indicators to assess market, price, and institutional integration across EU member states. Geweke and Porter-Hudak introduce long memory time series models, which capture persistent dependence and correlation structures over extended periods, enhancing our ability to model volatility clustering and trend persistence.

Additionally, studies by Ghosh (2002) and Kasa (1992) provide insights into the relationship between stock markets and economic activity, particularly in emerging economies and across international markets. Ghosh's research in India employs co-integration and causality analysis to uncover long-term equilibrium relationships between stock market indices and economic indicators, contributing to our understanding of financial market interactions in emerging markets. Kasa's study explores common stochastic trends across international stock markets, demonstrating the interconnectedness of global financial markets and the presence of common trend components among stock market indices.

Dutta (2018) explores the implied volatility linkages between the US and emerging equity markets, focusing on the transmission of volatility and its implications. The study finds significant connections, suggesting that volatility in the US market influences emerging markets, including India. The analysis highlights the importance of understanding these linkages for effective risk management and investment strategies. Choudhary and Singhal (2020) examine the international linkages of the Indian equity market using a panel co-integration approach. They find that Indian markets are co-integrated with global markets, indicating a long-term equilibrium relationship. This study underscores the interconnectedness of global financial markets and the implications for portfolio diversification and international investment decisions.

Collectively, these studies have enriched econometric methodology by providing rigorous frameworks for analyzing non-stationary time series data, testing for long-term relationships among variables, and understanding the dynamics of financial markets. They offer valuable insights for policymakers, researchers, and practitioners seeking to model and forecast economic and financial phenomena, thereby advancing our understanding of global economic dynamics and financial market interactions.

RESEARCH OBJECTIVES

The primary objective of this study is to analyze the dynamic relationships among financial market indices during both pre-COVID and COVID periods using econometric techniques. Specific research objectives include:

- To identify and analyze long-term equilibrium relationships (co-integration) among the financial market indices: Nifty 50, NIFTY100, NIFMDCP100, and NIFSMCP100.
- To assess the direction and strength of causal relationships among these indices using Granger causality tests.
- To compare and contrast these relationships between the pre-COVID and COVID periods, considering the impact of economic shocks and market dynamics.

DATA AND METHODS

This study utilized a comprehensive dataset spanning multiple years to analyze the dynamics of the Indian stock market. The data included daily closing prices of key indices such as Nifty 50, NIFTY100, NIFMDCP100, and NIFSMCP100, covering both pre-COVID and COVID-19 periods. The primary methodological approach involved three main techniques: co-integration analysis, Error Correction Models (ECMs), and Granger causality tests.

Co-integration analysis was employed to identify long-term equilibrium relationships among the indices. This technique helps determine whether these indices move together over extended periods, despite short-term fluctuations, indicating stable relationships. Error Correction Models (ECMs) were applied to model the adjustment process of the indices towards their equilibrium levels following deviations or shocks. ECMs are particularly useful for capturing both short-term dynamics and long-term relationships among variables. Granger causality tests were conducted to examine the direction and strength of causal relationships between the indices. This involved testing whether past values of one index can predict the future values of another, providing insights into the interdependencies among different segments of the stock market.

These methodologies were chosen for their robustness in handling non-stationary time series data and their ability to uncover the complex interactions within the Indian stock market under varying economic conditions. The study aimed to contribute to the understanding of financial market dynamics and provide valuable insights for investors and policymakers.

DATA ANALYSIS

Johansen Co-Integration Test

This test is a powerful tool for analyzing the long-term relationship between multiple time series. It helps us determine if there is a stable, long-run equilibrium relationship between the series, even if they exhibit short-term fluctuations.

Null Hypothesis: There is no co-integration relationship among Small cap stocks, Mid cap stocks, Large cap stocks, and the Nifty index.

Alternate Hypothesis: There is co-integration relationship among Small cap stocks, Mid cap stocks, Large cap stocks, and the Nifty index.

Table 1: Co-Integration Test Result across Segments Pre-COVID and COVID

Period	Index 1	Index 2	p-Value	Co-Integrated
Pre-COVID	Nifty 50	NIFTY100	0	True
Pre-COVID	Nifty 50	NIFMDCP100	0	True
Pre-COVID	Nifty 50	NIFSMCP100	0	True
Pre-COVID	NIFTY100	NIFMDCP100	0.983876	False
Pre-COVID	NIFTY100	NIFSMCP100	0.993575156	False
Pre-COVID	NIFMDCP100	NIFSMCP100	0.955551281	False
COVID	Nifty 50	NIFTY100	0	True
COVID	Nifty 50	NIFMDCP100	0	True
COVID	Nifty 50	NIFSMCP100	0.073749246	False
COVID	NIFTY100	NIFMDCP100	0.135418367	False
COVID	NIFTY100	NIFSMCP100	0.640855261	False
COVID	NIFMDCP100	NIFSMCP100	0.982750332	False

Interpretation of Pairwise Co-Integration Results

The analysis of pairwise co-integration between the indices Nifty 50, NIFTY100, NIFMDCP100, and NIFSMCP100 reveals differing behaviors during the pre-COVID and COVID periods.

Pre-COVID Period

During the pre-COVID period, the co-integration tests indicate strong long-term relationships among certain pairs of indices. Specifically, the pairs Nifty 50 - NIFTY100, Nifty 50 - NIFMDCP100, and Nifty 50 - NIFSMCP100 show p-values of 0, leading to the rejection of the null hypothesis of no co-integration. This suggests that these pairs are co-integrated, indicating that they moved together in the long run during this period.

On the other hand, the pairs NIFTY100 - NIFMDCP100, NIFTY100 - NIFSMCP100, and NIFMDCP100 - NIFSMCP100 have high p-values (0.983876, 0.993575156, and 0.955551281, respectively), which are above the 0.05 threshold. This means we fail to reject the null hypothesis of no co-integration for these pairs, indicating that they did not exhibit a long-term equilibrium relationship during the pre-COVID period.

COVID Period

In the COVID period, the co-integration landscape changes. The pairs Nifty 50 - NIFTY100 and Nifty 50 - NIFMDCP100 continue to show strong evidence of co-integration, with very low p-values of 1.84519E-05 and 1.75E-05, respectively. This indicates that these pairs maintained their long-term equilibrium relationships even during the heightened market volatility and uncertainty brought about by the COVID-19 pandemic.

However, the pair Nifty 50 - NIFSMCP100 shows a p-value of 0.073749246, which is above the 0.05 threshold, indicating no significant co-integration during the COVID period. Similarly, the pairs NIFTY100 - NIFMDCP100, NIFTY100 - NIFSMCP100, and NIFMDCP100 - NIFSMCP100 have p-values of 0.135418367, 0.640855261, and 0.982750332, respectively, all above the threshold. This lack of co-integration suggests that these pairs did not exhibit a stable long-term relationship during the COVID period, likely due to increased market instability and differing responses to the crisis.

Summary

In summary, the pre-COVID period saw robust co-integration between Nifty 50 and the other indices, indicating stable long-term relationships. However, several pairs, especially those not involving Nifty 50, did not exhibit co-integration. During the COVID period, only the relationships involving Nifty 50 and NIFTY100 or NIFMDCP100 remained strong, while other pairs lost their long-term equilibrium, reflecting the pandemic's disruptive impact on market dynamics. This analysis highlights the changing nature of market relationships in response to external shocks and underscores the importance of understanding these dynamics for investment and risk management strategies.

GRANGER CAUSALITY TEST

It is a statistical hypothesis test used to determine if one time series can predict another. Named after Clive Granger, who developed the concept, it's widely used in econometrics and time series analysis. The test assesses whether past values of one variable provide statistically significant information about future values of another variable beyond what is already known from the variable's own past values. It helps economists and analysts understand potential causal relationships between variables in dynamic systems.

Null Hypothesis (H0): The lagged values of one variable do not significantly improve the forecast of another variable.

Alternative Hypothesis (H1): The lagged values of one variable significantly improve the forecast of another variable.

Table 2: Granger Causality Test for Each Pair of Indices for Both the Pre-COVID and COVID Periods

Period	Cause	Effect	Min p-Value	Granger Causes
Pre-COVID	Nifty 50	NIFTY100	0.363367	False
Pre-COVID	Nifty 50	NIFMDCP100	0.67387	False
Pre-COVID	Nifty 50	NIFSMCP100	0.796827	False
Pre-COVID	NIFTY100	Nifty 50	7.57E-82	True
Pre-COVID	NIFTY100	NIFMDCP100	0.021265	True
Pre-COVID	NIFTY100	NIFSMCP100	0.221981	False
Pre-COVID	NIFMDCP100	Nifty 50	2.01E-44	True
Pre-COVID	NIFMDCP100	NIFTY100	0.408127	False
Pre-COVID	NIFMDCP100	NIFSMCP100	0.427958	False
Pre-COVID	NIFSMCP100	Nifty 50	2.68E-36	True

Period	Cause	Effect	Min p-Value	Granger Causes
Pre-COVID	NIFSMCP100	NIFTY100	0.073599	False
Pre-COVID	NIFSMCP100	NIFMDCP100	0.012342	True
COVID	Nifty 50	NIFTY100	0.182101	False
COVID	Nifty 50	NIFMDCP100	0.387476	False
COVID	Nifty 50	NIFSMCP100	0.476435	False
COVID	NIFTY100	Nifty 50	6.38E-124	True
COVID	NIFTY100	NIFMDCP100	8.60E-234	True
COVID	NIFTY100	NIFSMCP100	6.52E-164	True
COVID	NIFMDCP100	Nifty 50	1.40E-78	True
COVID	NIFMDCP100	NIFTY100	0.021154	True
COVID	NIFMDCP100	NIFSMCP100	0.147946	False
COVID	NIFSMCP100	Nifty 50	8.28E-58	True
COVID	NIFSMCP100	NIFTY100	0.076862	False
COVID	NIFSMCP100	NIFMDCP100	0.173012	False

Interpretation of Granger Causality Test Results

The Granger causality test results provide insights into the causal relationships among key indices (Nifty 50, NIFTY100, NIFMDCP100, and NIFSMCP100) during both the pre-COVID and COVID periods. During the pre-COVID period, Nifty 50 does not Granger-cause NIFTY100, NIFMDCP100, or NIFSMCP100, indicated by higher p-values (0.363367, 0.673870, 0.796827 respectively) and "FALSE" for Granger Causation. Conversely, NIFTY100 shows strong Granger causality towards Nifty 50 (p-value: 7.57E-82) and NIFMDCP100 (p-value: 0.021265), while NIFMDCP100 and NIFSMCP100 also exhibit significant causal relationships with Nifty 50. However, NIFSMCP100 does not Granger-cause NIFTY100 (p-value: 0.221981).

In the COVID period, Nifty 50 continues to show no significant Granger causality towards NIFTY100, NIFMDCP100, or NIFSMCP100, with higher p-values (0.182101, 0.387476, 0.476435) and "FALSE" for Granger Causation. Conversely, NIFTY100 demonstrates robust Granger causality towards Nifty 50 (p-value: 6.38E-124), NIFMDCP100 (p-value: 8.60E-234), and NIFSMCP100 (p-value: 6.52E-164), indicating strong causal relationships. Similarly, NIFMDCP100 shows strong Granger causality towards Nifty 50 (p-value: 1.40E-78) and NIFTY100 (p-value: 0.021154), while NIFSMCP100 exhibits significant Granger causality towards Nifty 50 (p-value: 8.28E-58). However, NIFSMCP100 does not Granger-cause NIFTY100 or NIFMDCP100 (p-values: 0.076862 and 0.173012, respectively).

In summary, these results highlight the evolving relationships among these indices, with the NIFTY100 index playing a pivotal role during the COVID period by showing strong Granger causality towards all other indices. This information is crucial for investors and policymakers to comprehend market dynamics during different economic periods and to devise effective strategies accordingly.

FINDINGS AND DISCUSSION

The Johansen Co-integration Test is a pivotal tool in econometrics used to assess enduring relationships among multiple time series variables. It aids in determining whether there exists a stable, long-term equilibrium relationship despite short-term fluctuations. In our study, we applied this test to analyze co-integration relationships among small-cap stocks, mid-cap stocks, large-cap stocks, and the Nifty index in the Indian stock market across two critical periods: the pre-COVID era and the COVID-19 pandemic.

During the pre-COVID period, our analysis unveiled varied degrees of co-integration among the studied indices. Pairs involving the Nifty 50 index—specifically Nifty 50 - NIFTY100, Nifty 50 - NIFMDCP100, and Nifty 50 - NIFSMCP100—exhibited strong evidence of co-integration with p-values approaching zero, rejecting the null hypothesis of no co-integration. This indicates that these pairs moved together in the long run, despite short-term market deviations.

Conversely, pairs not involving the Nifty 50 index—NIFTY100 - NIFMDCP100, NIFTY100 - NIFSMCP100, and NIFMDCP100 - NIFSMCP100—showed higher p-values above the 0.05 threshold. This suggests a lack of stable long-term relationships during the pre-COVID period, implying distinct market dynamics or independent movements among these segments.

In contrast, the COVID-19 pandemic introduced significant volatility and uncertainty, impacting co-integration relationships among the indices. While pairs involving the Nifty 50 index—Nifty 50 - NIFTY100 and Nifty 50 -

NIFMDCP100—maintained robust co-integration with very low p-values, indicating stable long-term equilibrium relationships, Nifty 50 - NIFSMCP100 showed a slightly higher p-value of 0.073749246, just above the threshold. Similarly, pairs like NIFTY100 - NIFMDCP100, NIFTY100 - NIFSMCP100, and NIFMDCP100 - NIFSMCP100 also displayed p-values above the threshold, suggesting disrupted long-term relationships during the pandemic.

The Granger causality test results reveal significant insights into the causal relationships among the Nifty 50, NIFTY100, NIFMDCP100, and NIFSMCP100 indices during both the pre-COVID and COVID periods. During the pre-COVID period, Nifty 50 does not exhibit Granger causality towards NIFTY100, NIFMDCP100, or NIFSMCP100, as indicated by higher p-values and “FALSE” for Granger Causation. Conversely, NIFTY100 shows strong Granger causation towards Nifty 50 and NIFMDCP100, while NIFMDCP100 and NIFSMCP100 also demonstrate causal relationships with Nifty 50 and each other to varying extents. Moving to the COVID period, NIFTY100 emerges as a dominant influencer, Granger-causing Nifty 50, NIFMDCP100, and NIFSMCP100 significantly. NIFMDCP100 continues to influence Nifty 50 and NIFTY100, albeit with weaker significance towards NIFSMCP100. Meanwhile, NIFSMCP100 shows strong causation towards Nifty 50 but lacks significant influence over NIFTY100 and NIFMDCP100. These findings underscore the dynamic nature of inter-index relationships, particularly highlighting the pivotal role of the NIFTY100 index during the COVID period. Such insights are crucial for stakeholders in finance and policymaking to navigate and strategize amidst changing market dynamics.

CONCLUSION

The Johansen Co-integration Test provided valuable insights into the long-term relationships among key indices in the Indian stock market across both the pre-COVID and COVID-19 periods. During the pre-COVID era, the Nifty 50 index demonstrated strong co-integration with NIFTY100, NIFMDCP100, and NIFSMCP100, indicating stable long-term relationships despite short-term market fluctuations. In contrast, indices not involving the Nifty 50 showed less consistent co-integration, suggesting more independent movements.

The onset of the COVID-19 pandemic significantly impacted these relationships. While the Nifty 50 maintained robust co-integration with NIFTY100 and NIFMDCP100, indicating continued stability in their long-term relationships, other pairs, including Nifty 50 - NIFSMCP100 and various pairs not involving the Nifty 50, exhibited weakened or non-existent co-integration. This shift underscores the pandemic’s disruptive influence on market dynamics and the varying degrees of interdependence among different market segments.

These findings are crucial for investors, policymakers, and analysts navigating the evolving landscape of the Indian stock market. Understanding these long-term relationships can assist in forming more informed investment strategies and policy decisions, especially in times of heightened market volatility and uncertainty. Future research could further explore the evolving nature of these relationships under different economic conditions to enhance our understanding of market behavior and dynamics.

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