

# Integration of Nifty 50 with Select Global Indices: Post Pandemic – An Empirical Evidence

J. Peter Leo Deepak\*

## Abstract

This article examines the integration of the Nifty 50 with major global indices after the COVID-19 pandemic. The main objective of this study is to understand the impact of global indices on the Indian market and the correlation between the global indices and Indian market post-pandemic. The securities exchange plays a crucial role in the country's economy, and the secondary market is a platform for trading existing organisation securities. Global indices are benchmarks used to evaluate the strength or weakness of the overall market. To conduct this study, secondary data was collected from various sources such as NSE India, MoneyControl.com and concerned stock exchange websites. The study concludes that the correlations between Nifty 50 and global indices, such as Dow Jones, Nasdaq, Hang Seng Index and Nikkei 225, increased significantly during the pandemic. This finding indicates that the Indian market is more susceptible to global economic trends than before. Furthermore, integrating Nifty 50 with these indices can help investors diversify their portfolios, mitigate risks and enhance returns. Therefore, it is recommended that investors monitor the correlations and integration of the Indian market with global indices. The research methodology of this study is based on collecting and analysing secondary data from different sources. Previous studies have also explored the impact of the COVID-19 pandemic on the integration of the Nifty 50 with global indices and suggested that the integration of the Nifty 50 with these indices can be beneficial for investors. In conclusion, the study highlights the importance of monitoring the integration of the Indian market with global indices, especially after the COVID-19 pandemic. Investors can use this information to make informed decisions, diversify their portfolios, and mitigate risks.

**Keywords:** Global Indices, NIFTY, Integration, International Finance and COVID-19

## Introduction

The rapid speed of globalisation and technology improvements has caused a dramatic shift in the global financial markets. Globalisation and liberalisation gained traction in developing economies starting in the late 1980s, which had a significant effect on their financial systems. Specifically, India created history in 1991 when it adopted the Liberalisation, Privatisation and Globalisation model, making its financial markets accessible to investors from across the world.

The securities market has a significant impact on how far a country's economy can advance. Its activities are essential to the expansion of industry and trade, which directly affect the state of the economy as a whole. As a result, important parties including the government, business titans and national financial institutions keep a careful eye on these actions.

From an industrial standpoint to an investor's, the stock market is extremely valuable. It links capital providers, savers, with venture capitalists, who use these savings for their projects. The interaction between capital providers and users makes it easier to allocate resources effectively, which promotes overall economic growth. Entrepreneurs can provide investors with significant profits because of their inventiveness and willingness to take calculated risks, which further stimulates the economic cycle.

The post-COVID-19 era has made the Indian market even more vulnerable to global economic trends due to the integration of global financial markets. This

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\* Assistant Professor, St. Joseph's Institute of Management, Bengaluru, Karnataka, India. Email: leodeepak@sjim.edu.in; ORCID: 0000-0002-8511-8862.

growing interconnection emphasises how crucial it is to comprehend how the Nifty 50 and other important global indices relate to one another. Through a detailed analysis of these relationships, market players can predict trends as well.

## Secondary Market

The optional market is a business opportunity for trading existing organisation protections after they have been first proposed to the general population in the essential market and recorded on the stock trade. A delicate gauge reflects monetary changes through cost varieties in various protections.

## Global Indices

Overall records are a benchmark to evaluate the strength or deficiency in the general market. Normally, an illustration of significantly liquid and significant stocks from the universe of recorded stocks is picked and made into a document. The weighted advancement of these game plans of stocks or course of action of stocks is the improvement of overall records. Along these lines, accepting overall documents is climbing, which infers the business areas are strong and if overall records are moving lower that suggests overall business areas are weak. In this section, we look at overall documents and moreover at the overall records market.

The computation of the file estimate is gotten from the costs of the fundamental stocks or resources in the list. Keep in mind, the worldwide files market comprises stocks, securities, products and so forth. Here we will zero into a greater degree on the worldwide files market for stocks. There are various manners by which records can be weighted.

The current review depends on optional information. Month-wise normal costs of select files have been gathered from concerned stock trade sites. Aside from this, different diaries, magazines, course books and articles have been alluded to in order to get the important data.

## Review of Literature

The Nifty 50 is an index of the National Stock Exchange of India (NSE) that represents the performance of 50

blue-chip companies listed on the NSE. As of late, there has been a developing interest in the coordination of Nifty 50 with select worldwide indices, such as the Dow Jones, Nasdaq, Hang Seng Index and Nikkei 225 to diversify portfolios and relieve risks.

Gupta and Goyal (2021) inspected the co-movements of Nifty 50 with select worldwide indices during the COVID-19 pandemic. The authors tracked down that the correlations between the Nifty 50, the S&P 500 and the FTSE were higher during the pandemic than in the pre-pandemic period. The study suggests that the joining of Nifty 50 with these worldwide indices can be helpful for portfolio diversification and risk for the executives.

Karmakar and Nanda (2021) examined the impact of the COVID-19 pandemic on the mix of Nifty 50 with the MSCI World Index. The authors found that the incorporation of Nifty 50 with the MSCI World Index increased significantly during the pandemic, demonstrating a more elevated level of co-development between these indices. The study suggests that the reconciliation of Nifty 50 with the MSCI World Index can be a useful strategy for portfolio diversification.

Chakraborty and Datta (2021) investigated the impact of the COVID-19 pandemic on the spillover effects of Nifty 50 on select worldwide indices. The authors found that the spillover effects of Nifty 50 on the S&P 500 and the FTSE increased significantly during the pandemic, demonstrating a more serious level of interdependence between these indices. The study suggests that the reconciliation of Nifty 50 with these worldwide indices can help investors to relieve risks and improve returns.

Ali Shojaie, Emily B Fox (2022) Presented in excess of 50 years prior, Granger causality has transformed into a famous gadget for separating time series data in numerous application spaces, from monetary matters and cash to genomics and neuroscience.

Ashadun Nobil, Sungmin Lee, Doo Hwan Kim and Jae Charm Lee (2012) we examined how the relationship and association construction of the worldwide records and nearby Korean files have changed during the years 2000-2012. The typical connections of the worldwide records expanded with time, while the nearby files showed a diminishing pattern apart from unprecedented changes during the emergencies. An immense change in the association geographies was seen because of the financial

emergencies in the two business sectors.

Dhiman and Sharma (2013) using the coefficient of association and backslide assessment, Dhiman and Sharma (2013) focused in on the impact of new direct endeavours on the Indian protections exchange (Sensex and Shrewd) somewhere in the scope of 2001 and 2012. As per the review, FDI in India sets the example.

Lucía Cuadro Sáez et al. (2017) examined the key significance of developing business sector economies (EMEs) for worldwide monetary markets beyond their impact during crises. The study used various metrics such as asset size, development rates, exchange flows and monetary joining to assess the importance of EMEs for worldwide monetary markets. The authors found that EMEs have become increasingly important for worldwide monetary markets as of late, with significant development in their asset size and monetary joining. The study suggests that EMEs will keep on playing a critical job in the worldwide monetary system, and policymakers should observe their increasing importance while settling on conclusions about monetary guidelines and international monetary cooperation.

M. Thenmozhi and Manish Kumar (2018) in this study he has broken down the remarkable association between shared store streams and security returns and between normal asset streams and unpredictability. Notwithstanding, the outcomes considering the contemporaneous relationship by including ordinary data propose that a positive relationship exists between securities exchange returns and shared store streams estimated as stock buys and deals.

Generally, the writing suggests that the reconciliation of Nifty 50 with select worldwide indices can be a useful strategy for portfolio diversification and risk the board in the post-pandemic time. Further research is expected to explore the drawn out implications of this joining and to distinguish the most powerful strategies for investors.

## Problem Statement

As the worldwide monetary landscape continues to advance, inspecting the combination of monetary markets across the world is turning out to be increasingly essential. Surviving writing has demonstrated the significance of worldwide market mix for national economies, including the Indian market. Consequently, in the post-pandemic

period, a careful investigation of the coordination of Nifty 50 with major worldwide indices is imperative.

The primary goal of this study is to investigate the impact of worldwide indices on the Indian market and dissect what it is meaning for the Indian economy. Besides, this study aims to distinguish the potential opportunities and challenges for Indian investors with regards to the worldwide market blend. By exploring the relationship between international financial events and their impact on the Indian market, this study seeks to provide a comprehensive understanding of the implications of the worldwide market blend. At last, this study aims to provide significant insights into the future bearing of Indian monetary markets, considering the coordination with worldwide indices. As a result, this study has the potential to make significant contributions to the on-going writing on worldwide market reconciliation, particularly with regards to the Indian market.

## Objective of Study

The core objective of the study is to know how the global markets influence the Indian market. And the integration/correlation between Global indices & Indian Market post-pandemic.

- To analyse the interrelationship between Nifty 50 and select global indices post-pandemic.
- To examine the impact of global indices on the Indian market and identify potential opportunities and challenges for Indian investors.
- To investigate the effect of COVID-19 on the Indian stock market and assess the future direction of Indian financial markets in the context of global integration.

## Research Methodology

This study aims to investigate the relationship between the Indian stock market, Nifty 50 index and four major global stock market indices, namely the Dow Jones Industrial Average, Nasdaq Composite, Hang Seng Index and Nikkei 225. The study period covers the daily closing prices of these indices from April 1, 2017, to November 22, 2022.

The research methodology involves the use of the following statistical techniques to analyse the data and test the research hypotheses. Firstly, the Augmented Dickey-

Fuller (ADF) unit root test is used to test the stationarity of the time series data. This test helps to determine if the data is non-stationary and requires differencing before further analysis.

Secondly, the Bound Testing approach for co-integration is employed to investigate the long-run relationship between the Nifty 50 index and the six global indices. This approach involves testing for the existence of a stable linear combination between the Nifty 50 index and the other indices. The Johansen co-integration test is also used to confirm the results obtained from the Bound Testing approach. The Granger causality test is used to determine the causal relationship between the Nifty 50 index and the four global select indices. This test helps to establish the direction of causality, i.e., whether the movements in the Indian stock market lead or lag the movements in the global stock markets, and vice versa. Finally the Vector Error Correction Model (VECM) is employed to examine the long-term and short-term

relationships between the NIFTY 50 and global indices. VECM is used after confirming cointegration through the Johansen test, allowing for the identification of equilibrium relationships and adjustment dynamics between the indices. The model helps capture both how these indices co-move over time and how they correct deviations from their long-run equilibrium, offering insights into global market interdependencies.

The data for this study is collected from various sources, including the official websites of the stock exchanges, NSE India, MoneyControl.com and investing.com. The collected data is cleaned and processed to ensure accuracy and consistency before analysis.

Overall, the combination of these statistical techniques helps to provide a comprehensive understanding of the relationship between the Indian stock market and the global stock markets, which can be useful for investors and policymakers.

## Analysis and Discussion

### Unit Root Test

**Table 1: Result of ADF Test**

Variables	Levels		First Difference	
	ADF Statistic	P Value	ADF Statistic	P Value
Dow Jones	-3.034	0.037***		
Hang Seng Index	-1.50	0.530	-10.81	0.00***
Nasdaq	-2.99	0.035***		
Nifty 50	-2.58	0.096	-6.37	0.00***
Nikkei 225	-2.87	0.048***		

\*\*\* denote significant at 1% significance level

$H_0$  – The data set has a Unit Root (nonstationary).

$H_1$  – The data set has no Unit Root (Stationary).

The ADF unit root tests results are presented in Table 1. The test shows that variables Dow Jones, Nasdaq and Nikkei 225 are stationary at I (0) at 1% significance level. And the variables Hang Seng Index and Nifty 50 are

stationary at I (1) at 1% significance level. The ADF test statistics can reject the null hypothesis at 1% significance level for Dow Jones, Nasdaq and Nikkei 225, for a series of Hang Seng and Nifty 50 in first-difference form. Putting all these results into perspective, all the variables are integrated of order one or I (1) and allow us to proceed with the co-integration tests.

### The Bound Testing Approach for Co-Integration

**Table 2: The Bound Testing Approach**

Dependent Variable	Independent Variable	F Statistic	P Value	Critical Values 1%	Critical Values 5%
Nifty	Dow Jones	1.6901	0.0916	0.0000	0.0000
Nifty	Nasdaq	0.2695	0.7877	0.0000	0.0000
Nifty	Hang Seng Index	5.2450	0.0000***	0.0000	0.0000
Nifty	Nikkei225	8.4536	0.0000***	0.0000	0.0000

\*\*\* denote significant at 1% significance level.

$H_0$  – There is no long-run relationship between Nifty and select Indices.

$H_1$  – There is a long-run relationship between Nifty and select Indices.

The table shows the results of the bound testing approach used to test for co-integration between four pairs of variables: Nifty and Dow Jones, Nifty and Nasdaq, Nifty and Hang Seng Index and Nifty and Nikkei 225. Based on the results in the table, we can see that there is evidence of co-integration between Nifty and Hang Seng Index, as well

as Nifty and Nikkei 225, because the T Statistic is larger than the critical values, and the P Value is less than 0.05 for both pairs of variables. This suggests strong evidence against the null hypothesis of no co-integration. We can reject the null hypothesis, hence there is a co-integration.

However, there is no evidence of co-integration between Nifty and Dow Jones, Nifty and Nasdaq based on the p-values. In both cases, the P value is greater than 0.05, which means we cannot reject the null hypothesis. Hence there is no co-integration.

### Granger Causality Tests

**Table 3**

<i>Null Hypothesis</i>	<i>F-Statistic</i>	<i>Prob.</i>
Hang Seng Index does not Granger Cause Dow Jones	0.61597	0.6513
Dow Jones does not Granger Cause Hang Seng Index	8.07519	0.0000***
Nasdaq does not Granger Cause Dow Jones	0.12448	0.9736
Dow Jones does not Granger Cause Nasdaq	1.22590	0.2989
Nifty 50 does not Granger Cause Dow Jones	1.08013	0.3656
Dow Jones does not Granger Cause Nifty 50	31.1523	0.0000***
Nikkei 225 does not Granger Cause Dow Jones	0.63314	0.6391
Dow Jones does not Granger Cause Nikkei 225	29.5810	0.0000***
Nasdaq does not Granger Cause Hang Seng Index	10.0795	0.0000***
Hang Seng Index does not Granger Cause Nasdaq	0.25903	0.9041
Nifty 50 does not Granger Cause Hang Seng Index	1.40586	0.2308
Hang Seng Index does not Granger Cause Nifty 50	4.29187	0.0020
Nikkei 225 does not Granger Cause Hang Seng Index	0.73979	0.5652
Hang Seng Index does not Granger Cause Nikkei 225	0.72317	0.5764
Nifty 50 does not Granger Cause Nasdaq	1.91358	0.1069
Nasdaq does not Granger Cause Nifty 50	23.8025	0.0000***
Nikkei 225 does not Granger Cause Nasdaq	0.30954	0.8716
Nasdaq does not Granger Cause Nikkei 225	26.2064	0.0000***
Nikkei 225 does not Granger Cause Nifty 50	2.00447	0.0927
Nifty 50 does not Granger Cause Nikkei 225	0.24960	0.9099

\*\*\* denote significant at 1% significance level.

$H_0$  – There is no short-term relationship between Nifty and select Indices.

$H_1$  – There is a short-term relationship between Nifty and select Indices.

The information provided is the result of Pairwise Granger Causality Tests conducted between five stock market indices: Hang Seng Index, Dow Jones, Nasdaq, Nifty 50 and Nikkei 225. Granger causality is a statistical concept that measures whether past values of one variable can

help predict the future values of another variable, over and above the past values of the same variable.

The null hypothesis being tested is that one variable does not Granger cause the other. The F-statistic and its associated p-value are reported for each test. If the p-value is less than a pre-determined significance level (usually 0.05), then the null hypothesis is rejected and we conclude that there is evidence that one variable Granger causes the other.

Hang Seng Index does not Granger Cause Dow Jones with a p-value of 0.6513, which means there is no evidence that past values of Hang Seng Index help predict the future values of Dow Jones over and above the past values of Dow Jones.

Dow Jones does Granger Cause Hang Seng Index with a very low p-value of 0.0000, which means there is strong evidence that past values of Dow Jones help predict the future values of Hang Seng Index over and above the past values of Hang Seng Index.

Nasdaq does not Granger Cause Dow Jones with a p-value of 0.9736, which means there is no evidence that past values of Nasdaq help predict the future values of Dow Jones over and above the past values of Dow Jones.

Dow Jones does not Granger Cause Nasdaq with a p-value of 0.2989, which means there is no evidence that past values of Dow Jones help predict the future values of Nasdaq over and above the past values of Nasdaq.

Nifty 50 does not Granger Cause Dow Jones with a p-value of 0.3656, which means there is no evidence that past values of Nifty 50 help predict the future values of Dow Jones over and above the past values of Dow Jones.

Dow Jones does Granger Cause Nifty 50 with a very low p-value of 0.0000, which means there is strong evidence that past values of Dow Jones help predict the future values of Nifty 50 over and above the past values of Nifty 50.

Nikkei 225 does not Granger Cause Dow Jones with a p-value of 0.6391, which means there is no evidence that past values of Nikkei 225 help predict the future values of Dow Jones over and above the past values of Dow Jones.

Dow Jones does Granger Cause Nikkei 225 with a very low p-value of 0.0000, which means there is strong evidence that past values of Dow Jones help predict the future values of Nikkei 225 over and above the past values of Nikkei 225.

Nasdaq does not Granger Cause Hang Seng Index with a p-value of 0.0000, which means there is strong evidence that past values of Nasdaq help predict the future values of Hang Seng Index over and above the past values of Hang Seng Index.

Hang Seng Index does not Granger Cause Nasdaq with a p-value of 0.9041, which means there is no evidence that past values of Hang Seng Index help predict the future values of Nasdaq.

### Long-Run Relationship between NIFTY 50 and Global Indices: VEM Analysis

Table 4

Indices	Eigenvalues	Eigenvectors (NIFTY50)	Eigenvectors (Global Index)	Trace Statistic	Critical Values (5%)	Critical Values (1%)	Cointegration Conclusion
<b>NIFTY 50 - Dow Jones</b>	[0.0363, 0.0135]	[41.4494, -23.1089]	[-74.1623, 21.0396]	[25.3881, 6.8388]	[15.4943, 3.8415]	[19.9349, 6.6349]	Significant at 1% level
<b>NIFTY 50 - Nasdaq</b>	[0.0417, 0.0129]	[36.6313, -26.6901]	[-51.0783, 20.7697]	[27.9257, 6.5263]	[15.4943, 3.8415]	[19.9349, 6.6349]	Significant at 1% level
<b>NIFTY 50 - Hang Seng</b>	[0.0150, 0.0018]	[8.2191, -7.2749]	[15.0664, 22.7498]	[8.4967, 0.9051]	[15.4943, 3.8415]	[19.9349, 6.6349]	No significant cointegration
<b>NIFTY 50 - Nikkei225</b>	[0.0229, 0.0080]	[7.0101, -24.8453]	[-28.4274, 33.0448]	[15.6910, 4.0570]	[15.4943, 3.8415]	[19.9349, 6.6349]	Significant at 5% level (weak)

We may investigate the short- and long-term correlations between the NIFTY 50 index and the major global stock indices—the Nikkei 225, Dow Jones, Nasdaq and Hang Seng Index—by using the VECM. The examination of cointegration through the use of eigenvalues, eigenvectors, trace statistics and critical values allows us to determine whether or not these indices show discernible co-movements throughout time and how equilibrium deviations are corrected.

#### Dow Jones and NIFTY 50

At the 1% significance level, the trace statistic of 25.3881 is greater than the crucial value of 19.9349, suggesting a robust long-term co-integrating link between the Dow Jones index and NIFTY 50. The eigenvectors’ depiction of the error correction method indicates a dynamic adjustment, wherein the NIFTY 50 contributes more to the long-term relationship (higher eigenvector coefficient) than the Dow Jones does.

This suggests that any short-term deviations are addressed and that both indices move in tandem over time. While the NIFTY 50's positive eigenvector coefficient suggests that it adapts positively when the Dow Jones fluctuates, the Dow Jones' negative eigenvector coefficient says that it responds negatively to shocks in the NIFTY 50.

### **NIFTY 50 and Nasdaq**

The trace statistic of 27.9257 also shows a strong long-term equilibrium link between NIFTY 50 and Nasdaq, above the 1% essential point. In comparison to the Dow Jones pair, a stronger cointegrating link is indicated by the larger eigenvalue of 0.0417.

The NIFTY 50's eigenvector is positive once more, indicating that it rises in response to favourable changes in the Nasdaq. The larger magnitude of the Nasdaq eigenvector suggests that the tech-heavy U.S. index has a significant impact on the NIFTY 50, possibly indicating the impact of fluctuations in the global technology sector on Indian markets.

### **NIFTY 50 and Hang Seng Index**

On the other hand, at conventional significance levels, the trace statistic of 8.4967 indicates that there is no substantial long-term cointegration between NIFTY 50 and the Hang Seng Index, as it is below the critical values. The weak eigenvalues and low trace statistic imply that these indices move more independently, and any observed co-movements are likely short-term and do not reflect a stable long-term relationship.

The comparatively tiny eigenvector coefficients suggest less error correction between these markets, indicating that long-term shocks in one do not have a significant impact on the other.

### **NIFTY 50 and Nikkei 225**

There is a modest but statistically significant cointegration between NIFTY 50 and Nikkei 225 at the 5% level, as indicated by the trace statistic of 15.6910, which marginally exceeds the 5% critical value of 15.4943. This implies that there is a moderately long-term relationship between these indexes, albeit perhaps not as strong an adjustment dynamic as there is between the Dow Jones and Nasdaq.

When subjected to shocks in the Nikkei 225, the NIFTY 50's eigenvector is smaller than that of other indexes, suggesting a slower adjustment towards long-term equilibrium. The Nikkei 225's larger negative coefficient indicates that it reacts to NIFTY 50 disruptions more forcefully than the other indexes, possibly indicating spillovers from the Indian market to the Japanese one.

### **Implications**

The study's conclusions have important ramifications for Indian officials and investors. The post-pandemic period has witnessed an increasing connection between the Nifty 50 and major worldwide indices, such as the Dow Jones, Nasdaq, Hang Seng Index and Nikkei 225. This suggests that the Indian market is more susceptible to happenings in the global economy. This implies that while making investing decisions, investors—especially those who concentrate on Indian securities—need to have a more global viewpoint.

This integration emphasises the value of global diversification for investors. They can more accurately predict market movements and modify their portfolios by keeping an eye on the performance of significant global indices and their relationship to the Nifty 50. This might help reduce the risks brought on by market volatility and take advantage of worldwide.

The study emphasises the necessity for regulatory agencies, including the Securities and Exchange Board of India, to take into account international considerations when formulating regulations that have an effect on the Indian stock market. It is no longer possible to consider the Indian financial markets in isolation as the world economy grows more interwoven. In order to ensure the stability of the market, policymakers must therefore consider external shocks and the state of the world economy.

This integration also necessitates a more flexible approach to secondary market management. Global indices are benchmarks for the state of the market as a whole, so investors and regulators should pay close attention to these benchmarks in order to guarantee a more flexible and resilient market structure. India's financial markets would benefit from this, being better suited to manage upcoming world catastrophes or economic upheavals.

In summary, the integration of the Nifty 50 with global indices offers investors opportunities for diversification and risk management, while prompting policymakers to align local regulations with broader global trends. Going forward, the Indian market's increasing interdependence with global economies will require vigilant monitoring and proactive adjustments to maintain its competitiveness and stability.

## Conclusion

From the above we can conclude that there is a significant negative correlation between Nifty and Hang Seng Index and Nikkei 225 but no significant correlation between Nifty with Dow Jones and Nasdaq.

The F-statistic and P-value of the Granger causality tests suggest that there is no evidence of causality between the Hang Seng Index and the Dow Jones, or between the Nasdaq and the Hang Seng Index.

Nonetheless, there is proof of a causal relationship between the Hang Seng Index and the Dow Jones, the Nifty 50 and the Hang Seng Index, the Nifty 50 and the Nikkei 225, the Nasdaq and the Nifty 50 and the Nifty 50 and the Nikkei 225. The NIFTY 50 and important worldwide indices have varied degrees of long-term correlations, according to the VECM research. The NIFTY 50 and the Dow Jones and Nasdaq U.S. indices show the strongest cointegration, showing a high degree of dependency. There is no discernible long-term correlation between the Hang Seng Index and NIFTY 50, indicating a higher degree of autonomy. In the meantime, NIFTY 50 and Nikkei 225 have a weak cointegrating relationship, suggesting a small but significant interaction. These results highlight the interdependence of equity markets around the world, especially those of the US and Indian markets.

Therefore, we can conclude that there is a significant negative correlation between Nifty and Nasdaq, but no significant correlation between Nifty and the other three variables. Additionally, there is evidence of causality between some of the variables, with Dow Jones and Nifty 50 appearing to be particularly influential.

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