The Interdependencies between Indian and Global Stock Markets: A Cointegration and Causality Analysis

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Abstract

Financial markets are a function of multiplicity of factors, which is a mix of both domestic and global factors. Company specific domestic and international factors do impact the stock market, however macroeconomic factors affecting one country and measurement of its impact on other country's stock market is an area of research. Studying the interdependencies can help an investor to take informed decisions and also allow corporate bodies to identify the opportune time for raising funds through capital markets. With the aim of understanding the cointegrating and causal relationships, the present study has been done investigating the cointegrating and causal relationship that FTSE 100, NASDAQ and NYSE have on Nifty. The sample consists of month wise data from 1st January 2005 to 1st June 2023. Unit root tests were employed to check for stationarity followed by Johansen's Cointegration test for checking cointegration. Further, VAR model, Wald test, and other explanatory tests were used to understand short run dynamics of the system. Pair-wise causality test has been performed for comprehending the effective causality that variables have on each other. Eviews12 Student version was employed for conducting the tests for the study. The findings suggest absence of cointegration and no evidence for short-term relationship or causality. The findings imply independence of Indian capital market, thereby explaining the growing confidence of foreign investors.

Keywords: Cointegration, causality, FTSE 100, NASDAQ, NYSE, NIFTY, VAR, Granger Causality, Eviews12

JEL classification: C12, C23, C32, C88, G15

Introduction

In today's highly interconnected and globalized economy, understanding the relationships between different stock indices has become increasingly vital. The global financial landscape is shaped by a myriad of factors, including geopolitical events, economic trends, and technological advancements. This research paper aims to delve deeper into the profound relationship between three prominent stock indices – Nasdaq, FTSE 100 and NYSE - and the NIFTY in India. By conducting a comprehensive analysis of the intermarket relationships between these indices, this study seeks to provide a nuanced understanding of the dynamics within international financial markets. The Nasdaq Composite Index holds immense significance in the world of finance, given its pioneering role as the first electronic stock exchange. It has evolved into a powerhouse for technology-based companies and has become synonymous with innovation and disruption. With a focus on technology giants such as Apple, Microsoft, Amazon, and Google, the Nasdaq Composite Index has gained recognition as a key barometer for global sentiment in the technology sector. As India's technology sector experiences rapid growth, driven by advancements in areas like artificial intelligence, cloud computing, and fintech, the performance of the Nasdaq index can serve as a crucial indicator of the health and potential of Indian technology stocks. Understanding the interrelationship between the Nasdaq and the Nifty can provide valuable insights into the trends and sentiments within India's technology-driven industries. FTSE 100 is a representative index of the London Stock Exchange, comprising of the top hundred listed organisations according to market capitalization, and serves as a prominent benchmark index for the United Kingdom. This index covers a diverse range of industries, including finance, mining, pharmaceuticals, consumer goods, and more. As a reflection of the wholistic health of the UK economic status and investor sentiment in the region, the FTSE 100 plays a pivotal role in shaping global investment decisions. Considering the close trade partnerships, investments, and cultural ties between India and the United Kingdom, the influence of the FTSE 100 on the Nifty cannot be underestimated. Analysing the relationship between these indices can provide crucial insights into the economic and financial interrelationships between the two countries and the probable effect on the securities market of India. The NYSE stands as the world's largest stock exchange, serving as a primary platform for numerous well-established companies, including blue-chip stocks and conglomerates. The performance of the NYSE carries substantial weight in shaping global investor sentiment, providing insights into the economic status of the U.S. and the financial system around the world. Given the existing financial relationship and eco-political ties between the Indian sub-continent and the US, the influence of the NYSE on the Nifty is of great significance. Additionally, the attractiveness of Indian equities to foreign investors further strengthens the connection between the NYSE and the Nifty. Analysing the relationship between these indices allows for a deeper understanding of the influence of changes in the NYSE on the Nifty. The Nifty serves as the standard stock index of the NSE India, encompassing 50 of the largest and most actively traded companies in the country. These companies represent various sectors, including information technology, finance, energy, and consumer goods, making the Nifty a comprehensive reflection of the stock market of India. Analysing the interrelationships among the Nasdaq, FTSE 100, NYSE and the Nifty is essential for investors and researchers seeking a comprehensive understanding of the dynamic financial landscape worldwide and its effect on India's capital market. By investigating the consequential interconnection amongst Nifty and the selected global indices, this research paper aims to unlock valuable insights into the dynamics of these interrelationships. These findings are crucial for fund providers, capitalists, stakeholders, policymakers, and financial firms, enabling them to make informed decisions, manage risks, and capitalize on opportunities emerging from the interconnectedness of international financial markets. Furthermore, this research contributes to the broader understanding of the global economy, helping to navigate the complexities of international finance and drive sustainable growth in the ever-evolving world of investments.

Literature Review

The connection and incorporation of Indian securities market with international securities markets have captured the attention of both scholars and investors. This literature review is presented with the aim to provide a comprehensive summary of numerous scholarly papers investigating the correlated movements in-between the Indian equity share market and diverse global equity share markets, encompassing the US, Asian, European, and other emerging markets. Nath & Verma (2003) examined the dependencies of the Indian, Singaporean, and Taiwanese stock markets among each other. Their analysis reveals absence of cointegrating relationship among the indices of capital markets throughout the period of study, suggesting the lack of long run relationship. The scholarly paper suggests that equity share markets in India, Singapore, and Taiwan are not strongly interdependent, and investors should consider this when making investment decisions. Ahmad et al. (2005) examines the interlinkages and causal inter-relatedness among the securities markets of USA and Japanese with the India's equity markets. The analysis reveals non-existent long-run association of the Indian capital market with the capital markets of US and Japan. The study's conclusion is that the markets are separated, allowing opportunities for diversifying investments. Venkata (2006) investigates the sustained balance of Indian capital markets and both advanced and emerging economies, as well as the transient interconnections in the short term. The study finds bidirectional and unidirectional causal association between the capital markets, with different lag periods. Menon et al. (2009) investigated the stability and sustainability of relationship in the long run of the index of Indian securities market along with leading equity share markets using the Engle Granger test. Results of the scholarly paper reveals that the domestic securities market shares cointegrating relationships with some of the markets around the world but not to the US securities market. The findings indicate autonomous functioning of Indian capital market. Chittedi (2010) investigates the level of integration among the domestic capital market with countries such as the USA, UK, Japan, France, and Australia. The research discovers co-integrating relationship of India with USA, Japan, and France. It suggests that these international capital markets influence the Indian capital market significantly. Subha & Nambi (2010) examines the degree of integrating association among the securities market of India and the American securities markets. The study finds substantial degree of cointegration among the domestic equity market and the US equity market. It suggests that the Indian equity share market is interdependent on the American equity share markets. Sakthivel (2012) considered Asian, European and US equity markets for investigating interlinkages among amongst them. The research reveals robust interconnectedness among these markets and emphasizes US markets' effect on the Indian market returns. The study also identifies the evolution of the linkages and the time varying relationships among the different capital markets. Patel (2013) investigates dynamic association and co-movements of first-world capital markets with the Indian capital market. The research uncovers an absence of long-term equilibrium connection among the capital markets. It suggests that in case of India, the market is affected only by self-lagged values, and other developed equity markets have no Granger causality on it. Patel (2014) investigates the dynamic connections between the Indian equity share market with other similar markets in the Asian region. Findings indicate dynamic linkages amongst the domestic share market and other Asian share markets. It suggests that cross-border investment can be used to diversify portfolios, but caution is needed before generalizing the results. Thangamuthu & Parthasarathy (2015) examine the cointegration and interdependence of stock markets in India, South Africa, and the USA. The study finds presence of cointegrating association among these markets, indicating a long-term relationship. The study proposes that investors can gain advantages from diversifying their portfolios across these markets. Veerappa (2016) examines the integrating relationships of largest Asian share markets, including India. Findings of the study suggest a significant time varying association among these markets, both in the short and long-run. The capital market of India is related in the long-run with other Asian stock markets, indicating a cointegrating relationship. Bhattacharjee & Swaminathan (2016) investigates how India's stock market integrates with specific countries worldwide. The findings indicate a progressive improvement in domestic capital market integration with global economy over time. India's policy initiatives to liberalize its financial markets attract foreign investment worked in its favour. Singh (2017) explores the interconnections and associations of returns among the stock exchanges of advanced economies and the Indian stock market. Results reveal both one-way and two-way causal connections existing betwixt the Indian equity share market and other well-developed equity share markets. Moreover, it implies that integration in the markets of Asia is due to Indian capital market's unique role. Deo et al. (2017) investigates the co-integration of equity market in India with major global equity markets. The study finds association in the longer period among the domestic capital market and other stock exchanges around the world. The findings indicate that investors can gain advantages by diversifying their investments across these markets. Goyal & Bansal (2019) studied the time varying relationship in-between the Indian and US capital markets through multiple econometric tests. The results provided evidence for non-existence relationship in the long run among markets. Nonetheless, it was observed that US capital market causes movements in the capital market of India, suggesting that the returns of the US market impact the Indian market returns. Rizwanullah et al. (2020) studied the time varying interrelation in the eight largest capital markets of Asia. They find strong cointegrating relationship among these markets in the long run and identify both bidirectional and unidirectional causality relationships. The integrated markets provide benefits such as diversification and the ability to absorb financial shocks. The literature review highlights the findings of various studies examining the interlinkages and co-integrating characteristic of the domestic financial market with global financial markets. While some studies find significant relationships and integration among the capital market of India and certain global capital markets, others find absence of time varying relationships or weak interdependence. Further explorations are required to have a deeper comprehension of the complexities and evolving relationships among global stock markets, including the Indian stock market.

Research Question: Does nifty 50 get impacted by changes in the top three largest stock market in the world?

Research Objective

Given recent world events such as the war between Ukraine and Russia, the cash crunch of the USA, and major interest rate revisions happening worldwide, the global economy is experiencing constant fluctuations. In light of these circumstances, it becomes crucial to periodically evaluate the associative characteristic among the Indian equity share market as measured by Nifty and other international financial markets. Therefore, purpose of this study is two-fold: first, to inquire into the presence of cointegration among the Nifty and the top three stock markets globally, and second, to determine if there are existence of causality among the Nifty and the other capital markets. Aim of this study is to assess whether the Nifty and the selected capital markets share a long-term equilibrium relationship, indicating their interdependence and the potential benefits of diversification. Cointegration analysis has been employed with an attempt in determining the presence of such a relationship, considering factors like economic integration and shared financial influences.

Additionally, the study explores the possibility of causality among Nifty and the other capital market indices. By making use of econometric techniques such as Granger causality tests, the study determines if the movements in the Nifty can be considered as a leading indicator or if it is impacted by other capital markets under consideration.

Methodology

Researchers considered monthly data of Nifty 50, Nasdaq, FTSE 100 (London Stock Exchange Index) and NYSE from January 2005 to June of 2023 collected from data repository of investing.com. There were a total of 888 observations with 222 observations from each factor in consideration. The variables were transformed to their logarithmic equivalents as it helps achieve linearity in the relationship. It was also done so that with such transformation the skewness and heteroskedasticity in the data can be addressed. Before proceeding with analysis, necessary step is to check for stochasticity of the time series data, for which unit-root tests were applied- Augmented Dickey Fuller Test (Dickey & Fuller, 1979), Phillips-Perron Test (Phillips & Perron, 1988) and Breakpoint Test (Perron, 1997). Augmented Dickey Fuller (ADF) test is a commonly performed econometric test to examine the stochasticity of time dependent variables. It is an improvised continuation of the Dickey-Fuller test, designed to handle more sophisticated and realistic situations. The ADF test is relies on the autoregressive model, assuming that past values have potential effect on present values of the variable. The null hypothesis is tested for existence of unit root, indicating stochasticity. The autoregressive behaviour of the data is accounted for by taking into consideration differenced form of lag variable in the equation. By taking differences between consecutive observations, it helps eliminate the presence of stochasticity. It examines the significance of the coefficient of the terms in the regression equation. If it is significant statistically, it suggests evidence against the presence of stochasticity and supports stationarity. The choice of ranges of lags is crucial. The SIC (Schwarz Information Criterion) automatically suggested by the Eviews12 econometrics software has been considered to select an appropriate lag length, taking into account the trade-off between model complexity and goodness-of-fit. The ADF test estimates using ordinary least squares (OLS) regression, whereas Phillips Perron (PP) Test is estimated using non-parametric regression. This test addresses serial correlation concerns by utilizing a Newey-West estimator, ensuring reliable constant estimates of standard errors even when autocorrelation is present. The PP test employs different critical values based on a modified version of the Dickey-Fuller distribution. These critical values account for the presence of serial correlation and provide more accurate inference. The Breakpoint Unit Root (BPU) test is employed along with the ADF and PP tests because of its ability to capture sudden changes causing abrupt shifts in time series data. Presence of such structural changes in time-dependent series can yield misleading outcomes in the previous two unit root tests if such breakpoints are not taken into consideration. The design of BPU test is to successfully identify structural breaks, which are changes in the underlying data-generating process over time. These breaks can arise due to shifts in economic policies, changes in market conditions, or other significant events. The ADF and PP tests, on the other hand, assume stationarity or a stable data-generating process without considering structural breaks explicitly. The BPU test allows for multiple breaks or regime shifts in the time series, which can be more realistic in capturing the dynamics of the data. It provides estimates of the break points and allows for different behaviours of the series before and after these breaks thereby providing more accurate estimates of the underlying data properties. This leads to improved statistical power and more reliable inference compared to the other two unit root tests. Following the test of stationarity lag order selection employing Vector Autoregression Model was done to find the appropriate lag length to conduct further tests. After which, to examine the presence of cointegration among multiple time series variables, cointegration test as suggested by Johansen was performed. Cointegration indicates a long-term relationship or equilibrium among variables, suggesting joint movement in the long term despite exhibiting short-term fluctuations. Johansen's cointegration test has Vector Autoregressive (VAR) model as its basis, which captures interdependencies among multiple variables over time. The VAR model depicts each variable as a linear equation comprising past values of both the variable itself and other independent variables. This approach allows for the inclusion of lagged variables in the formulation of the model to study their interdependencies and interactions over time without violating the integrity of original content. The test assesses the cointegration rank, which signifies the highest count of cointegrating vectors that are linearly independent among the variables. Cointegrating vectors are combinations of the variables with long-term equilibrium relationship. Johansen's cointegration test includes two statistical tests to assess the cointegration rank. The Trace test evaluates whether the null hypothesis, asserting a maximum number of vectors that exhibit long-term relationships, is valid compared to the alternative hypothesis proposing a reduced number of such vectors. The Maximum Eigenvalue test appraises the null hypothesis, which specifies a particular number of long-term related vectors, in contrast to the alternative hypothesis of a smaller number. Vector Autoregression (VAR) allows for the analysis of the dynamic interrelationships among multiple variables in a system considering each variables as endogenous. It is particularly useful for studying the simultaneous interactions and feedback effects between variables, making it a valuable tool for forecasting, policy analysis, and understanding complex economic phenomena. VAR models provide a flexible framework for analysing the complex interrelationships among multiple variables in an economic system. By capturing the dynamic interactions, feedback effects, and transmission mechanisms, VAR models offer valuable insights for understanding economic dynamics, forecasting, policy analysis, and exploring the complex web of relationships within an economic system. To identify the possibility of consecutive association in the VAR model's residuals, the correlation LM test for serial correlation was utilized. The existence of sequential dependence in the residuals of a VAR model suggests that the model fails to adequately capture the temporal interrelationships among the variables. A valid VAR model presupposes independent residual characteristics with identical distributions, having a mean of zero and a consistent variance. If serial correlation exists, it implies that there is some systematic pattern or structure in the residuals that the model has failed to capture, potentially leading to biased parameter estimates and misleading inferences. Serial correlation can invalidate the assumptions of classical linear regression, such as unbiasedness and efficiency of parameter estimates and the validity of hypothesis tests. When serial correlation is present, standard errors of the coefficients are biased, making it difficult to draw meaningful conclusions from the estimated relationships between the variables. By testing for serial correlation, reliability of the inference can be drawn from the VAR model results. After estimating a VAR, the significance of specific coefficients were tested to assess the significant relationships between the variables. This was done with the help of Wald test. It is a general test of hypothesis that allows to evaluate whether a set of coefficients is jointly equal to a specific value (usually zero, as is also considered in this study). The null hypothesis of coefficients are assumed to be equal to zero, implying that the corresponding variables do not affect each other. Once a Vector Autoregression (VAR) model has been estimated, the Impulse Response Function (IRF) becomes a fundamental tool for examining the dynamic relationships between the variables. The IRF provides valuable insights into how shocks to one variable affect the entire system over time. The computation of the IRF involves a recursive process. Initially, a shock is applied to the variable of interest, and the responses of all variables in the system are tracked over several periods. At each time step, the impact of the shock is propagated through the VAR model, taking into consideration the lagged effects of the shock in other variables. The process continues for a predetermined number of periods or until the responses become negligible. The IRF is typically plotted graphically, showing the responses of each variable to the initial shock over time. The response can be positive or negative, indicating the direction and magnitude of the impact, and may exhibit different patterns depending on the nature of the shocks and the system's dynamics. Following the Impulse Response Function (IRF) test, a bivariate Granger Causality Test was employed to evaluate the effectual connection among variables in a time varying observance. The foundation of this lies within the concept of Granger causality, which investigates whether past values of a particular variable offer valuable insights for forecasting another variable. The Granger causality test, conducted between pairs of variables, encompasses estimating individual autoregressive models for each variable of concern. Subsequently, it compares the forecasting ability of these models, both with and without the incorporation of lagged values from other variable(s). The objective is to determine if the inclusion of lagged values of one variable improves the prediction of the other variable beyond what can be achieved using only its own lagged values. It provides insights into the direction and strength of causality, helping to understand the dynamic interactions and dependencies within a system.

Hypothesis to be tested:

For testing cointegration:

H_{01}: The presumed hypothesis posits an absence of cointegration within Nifty and NASDAQ. In other words, Nifty and NASDAQ do not share a long-term equilibrium relationship, indicating that they are not interdependent.

H_{02}: The presumed hypothesis suggests an absence cointegration within Nifty and FTSE 100. This hypothesis assumes that Nifty and FTSE 100 do not exhibit a long-term equilibrium relationship and are not significantly interrelated.

H_{03}: The presumed hypothesis states an absence of cointegration among Nifty and NYSE. This hypothesis assumes that Nifty and NYSE do not possess a long-term equilibrium relationship and are not strongly connected.

For testing the causality:

H_{04}: The presumed hypothesis proposes no existence of causal relationship from NASDAQ to Nifty. In other words, the lagged values of NASDAQ do not significantly contribute to the prediction of Nifty, indicating the absence of a causal relationship from NASDAQ to Nifty.

H_{05}: The presumed hypothesis posits no existence of causal relationship from FTSE 100 to Nifty. This hypothesis assumes that the inclusion of lagged values of FTSE 100 does not significantly improve the prediction of Nifty, suggesting no causal relationship from FTSE 100 to Nifty.

H_{06}: The presumed hypothesis states no existence of causal relationship from NYSE to Nifty. This hypothesis assumes that the lagged values of NYSE do not provide valuable information in predicting Nifty, indicating no causal relationship from NYSE to Nifty.

These hypotheses form the basis for investigating the presence or absence of cointegration and causality between Nifty and the respective indices (NASDAQ, FTSE 100 and NYSE). The empirical analysis will involve applying appropriate statistical techniques to assess the statistical significance of these relationships and draw meaningful conclusions about the interdependencies and causal linkages between Nifty and the global indices.

Findings and Discussion

Unit Root Test

Table 1 displays the ADF test and PP test at level. The variables in consideration returned probability values greater than 0.05. This provides a contradiction in the result between ADF and PP test. The difference in results may arise due to structural breaks within the time series data and to counter that Breakpoint test was conducted and the summary result has been shown in Table 3. Clearly it is observed from the results the evidence of sudden shifts, hence testing the unit root accounting for the structural breaks give a result which reveals that all the variables fail to reject null at 5% significance level, that is, the variables are stochastic at logged form I(0). Table 2 and 3 exhibit the outcomes of the unit root tests conducted on the initial differentiation of all the variables. All three tests unanimously reject the null hypothesis at a significance level of 0.05. This implies that the variables within the time-dependent series display stationarity at the first-order difference.

Table 1

Unit Root Tests	**ADF, data at level**			
Specifications	**Automatic Lag-length according to SIC**			
Variables	**t-stat.**	**p-value.***	**5%**	**Null hypothesis**
FTSE 100	-2.167892	0.2188	-2.87444	Cannot reject null hypothesis
NASDAQ	0.048382	0.9610	-2.87444	Cannot reject null hypothesis
NIFTY	-1.307731	0.6262	-2.87444	Cannot reject null hypothesis
NYSE	-0.591338	0.8687	-2.87444	Cannot reject null hypothesis
Unit Root Tests	**PP, data at level**			
Specifications	**Bandwidth based on Newey-West automatic using Berrlett Kernel**			
Variables	**t-stat.**	**p-value***	**5%**	**Null hypothesis**
FTSE 100	-2.259574	0.1862	-2.87444	Cannot reject null hypothesis
NASDAQ	0.017826	0.9584	-2.87444	Cannot reject null hypothesis
NIFTY	-1.319649	0.6206	-2.87444	Cannot reject null hypothesis
NYSE	-0.7542	0.8293	-2.87444	Cannot reject null hypothesis

*p-values are one-sided according to MacKinnon (1996)

Source: Author's findings through tests conducted in Eviews12 student version, critical values for the study has been determined at 5% level of significance for testing.

Table 2

Unit Root Tests	ADF at 1st difference			
Specification	**Automatic Lag-length according to SIC**			
Variables	**t-stat.**	**p-value***	**5%**	**Null hypothesis**
FTSE 100	-14.82941	0	-2.8745	Reject null hypothesis
NASDAQ	-14.68874	0	-2.8745	Reject null hypothesis
NIFTY	-14.54397	0	-2.8745	Reject null hypothesis
NYSE	-13.64718	0	-2.8745	Reject null hypothesis
Unit Root Tests	**PP at 1st difference**			
Specification	**Bandwidth based on Newey-West automatic using Berrlett Kernel**			
Variables	**t-stat.**	**p-value***	**5%**	**Null hypothesis**
FTSE 100	-14.83174	0	-2.8745	Reject null hypothesis
NASDAQ	-14.69247	0	-2.8745	Reject null hypothesis
NIFTY	-14.54616	0	-2.8745	Reject null hypothesis
NYSE	-13.68054	0	-2.8745	Reject null hypothesis

* p-values are one-sided according to MacKinnon (1996)
Source: Author's findings through tests conducted in Eviews12 student version.

Table 3

Unit Root Test	Breakpoint Test at level				
Specifications	**Break Selection according to "Minimize Dickey-Fuller t-statistic"**				
	Automatic Lag-length according to SIC				
Variables	**Break Date**	**t-stat**	**p-value***	**5%**	**Null hypothesis**
FTSE 100	Jun-06	-3.40552	0.4379	-4.44365	Cannot reject null hypothesis

NASDAQ	Mar-09	-1.75627	>0.99	-4.44365	Cannot reject null hypothesis
NIFTY	May-20	-2.532636	0.8934	-4.44365	Cannot reject null hypothesis
NYSE	Nov-12	-2.602356	0.868	-4.44365	Cannot reject null hypothesis
Unit Root Test	**Breakpoint Test at 1st difference**				
Specifications	**Automatic Lag-length according to SIC**				
Variables	**t-stat.**		**p-value***	**5%**	**Null hypothesis**
FTSE 100	-15.86073		<0.01	-4.44365	Reject null hypothesis
NASDAQ	-15.65371		<0.01	-4.44365	Reject null hypothesis
NIFTY	-15.92552		<0.01	-4.44365	Reject null hypothesis
NYSE	-15.01886		<0.01	-4.44365	Reject null hypothesis

*p-values are one sided and according to Vogelsang(1993)
Source: Author's findings through tests conducted in Eviews12 student version, critical values for the study has been determined at 5% level of significance for testing.

Lag selection criteria

Following the unit root tests, lag order selection was conducted by first testing the VAR and selecting the appropriate lag length from lag selection criteria. Table 4 below demonstrates the result of lag length criteria for selecting appropriate lag. From the result SC or SIC (Schwarz Information Criteria) was chosen for further tests, which is lag 0. It is an indicator that there may not be any presence short run relationship among the variables, to confirm it further tests have been performed.

Table 4

Lag Selection Criteria (VAR)
Dependent variables: DLFTSE DLNASDAQ DLNIFTY DLNYSE
Independent variables: C
Sample: 2005M01 2023M06
213 observations have been included

Lag	**LogL**	**LR**	**FPE**	**AIC**	**SC**	**HQ**
0	1518.653	NA	7.83e-12*	-14.22210*	-14.15897*	-14.19659*
1	1524.009	10.45959	8.65e-12	-14.12215	-13.80653	-13.99460
2	1533.559	18.29320	9.19e-12	-14.06159	-13.49348	-13.83200
3	1538.983	10.18628	1.02e-11	-13.96228	-13.14169	-13.63065
4	1559.418	37.60818*	9.75e-12	-14.00393	-12.93084	-13.57026
5	1567.515	14.59656	1.05e-11	-13.92972	-12.60414	-13.39400
6	1573.805	11.10348	1.15e-11	-13.83854	-12.26047	-13.20079
7	1582.312	14.69800	1.24e-11	-13.76819	-11.93762	-13.02840
8	1590.826	14.39028	1.34e-11	-13.69790	-11.61484	-12.85607

*indicates each criterion's selection of appropriate lag length.
Source: Author's findings from test conducted in Eviews12 student version.

Johansen's Cointegration Test

Since the variables without exception are non-stochastic at first difference so Johansen's cointegration test was conducted with the aim of investigating the evidence for cointegration among variables. Table 5 displays the result of test. The test was measured under both Trace statistic and Max-Eigen statistic. The results reveal that for all the possibilities the absence of long run cointegration amongst the variables were evident because the probability values exceed 0.05, meaning, the presumed hypothesis of no cointegration cannot be rejected. This means that the hypothesis H_{01}, H_{02} and H_{03} cannot be rejected. Now, in the absence of conclusive evidence for cointegration amongst the variables short run relationship is to be tested with VAR model.

Table 5

Sample (adjusted): 2005M06 2023M06
217 adjusted observations were included
The trend is assumed to be a linear function of time, with a constant slope
Series: LFTSE LNASDAQ LNIFTY LNYSE
Lag interval 1 to 4 in first order difference

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Stat.	0.05_Critical Value	Prob.**
None	0.094942	39.80976	47.85613	0.2294
At most 1	0.043112	18.16255	29.79707	0.5541
At most 2	0.038726	8.599656	15.49471	0.4037
At most 3	0.000134	0.029078	3.841465	0.8645

Unrestricted Cointegration rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Stat.	0.05_Critical Value	Prob.**
None	0.094942	21.64721	27.58434	0.2390
At most 1	0.043112	9.562896	21.13162	0.7846
At most 2	0.038726	8.570578	14.26460	0.3236
At most 3	0.000134	0.029078	3.841465	0.8645

No cointegration at 5% level as per Max-eigenvalue
*hypothesis is rejected at 5% level
** p-values as per MacKinnon-Haug-Michelis (1999)

Source: Author's findings from test conducted in Eviews12 student version.

Vector Autoregression

Table 6 exhibits the test results of VAR. Upon evaluating the t-statistics and comparing with the tabulated values at 5% significant level, it becomes evident that none of the lagged variables significantly influence any of the variables, further supported by the result that no t-statistic for the variables exceeds the threshold of ± 1.96. This is in agreement with the lag order suggestion as VAR is calculated for lagged variables whereas the lag order suggested 0 lags. The results suggest no influence of one variable over the other in lagged form.

Table 6

Estimates of VAR				
Adjusted sample includes data from: 2005M04 2023M06				
219 adjusted observations have been included				
SE presented in ( ) & t-stat. presented in [ ]				
	DLFTSE	**DLNASDAQ**	**DLNIFTY**	**DLNYSE**
DLFTSE(-1)	-0.103796	-0.006666	0.052167	-0.026688
	(0.10548)	(0.14939)	(0.17431)	(0.15403)
	[-0.98405]	[-0.04462]	[0.29928]	[-0.17326]
DLFTSE(-2)	0.081353	-0.012269	-0.028394	0.055245
	(0.10503)	(0.14875)	(0.17375)	(0.15337)
	[0.77459]	[-0.08248]	[0.16359]	[0.36021]
DLNASDAQ(-1)	-0.032159	-0.109129	0.035849	0.024988
	(0.07974)	(0.11294)	(0.13178)	(0.11645)
	[-0.40329]	[-0.96629]	[0.27204]	[0.21459]
DLNASDAQ(-2)	-0.095013	0.056897	0.187297	-.0.013358
	(0.07929)	(0.11230)	(0.13103)	(0.11579)
	[-1.19829]	[0.50666]	[1.42938]	[-0.11536]
DLNIFTY(-1)	0.024134	0.067656	-0.057236	0.042379
	(0.05717)	(0.08097)	(0.09448)	(0.08349)
	[0.42214]	[0.83555]	[-0.60609]	[0.50760]
DLNIFTY(-2)	-0.016369	-0.082956	-0.048948	-0.103511
	(0.05722)	(0.08104)	(0.09456)	(0.08356)
	[-0.28608]	[-1.02366]	[-0.51765]	[-1.23880]
DLNYSE(-1)	0.120215	0.103821	0.078083	0.050332
	(0.06973)	(0.09875)	(0.11523)	(0.10182)
	[1.72409]	[1.05132]	[0.67763]	[0.49431]
DLNYSE(-2)	-0.050278	-0.008467	-0.179671	0.027541
	(0.06991)	(0.09902)	(0.11554)	(0.10210)
	[-0.71914]	[-0.08551]	[-1.55508]	[0.26976]
C	0.002524	0.008604	0.009584	0.004520
	(0.92706)	(0.00386)	(0.00450)	(0.00398)

	[0.92706]	[2.23124]	[2.13007]	[1.13667]

Source: Author's findings from test conducted in Eviews12 student version.

Lagrange Multiplier test for serial correlation

The VAR model validity and statistical efficiency has been evaluated by serial correlation LM test. Table 7 below displays the results. Accordingly, null hypothesis states an absence of serial correlation among the residuals of VAR. Probability values for lag 1 and 2 exceed 0.05, thereby making it impossible to reject the null hypothesis. This means, the serial correlation is absent from the residuals. This proves that the VAR model is a good fit.

Table 7

Residual of Vector Autoregression tested by Serial Correlation LM Test
Sample: 2005M01 2023M06
219 observations included

Null hypothesis: No serial correlation at lag h

Lag	LRE* Stat	df	Prob.	Rao F-stat	df	Prob.
1	9.450785	16	0.8937	0.588507	(16, 620.8)	0.8937
2	14.88758	16	0.5329	0.931095	(16, 620.8)	0.5329

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* Stat	df	Prob.	Rao F-stat	df	Prob.
1	9.450785	16	0.8937	0.588507	(16, 620.8)	0.8937
2	39.20324	32	0.1781	1.232527	(32, 735.5)	0.1783

*Edgeworth expansion corrected likelihood ratio statistic
Source: Author's findings from test conducted in Eviews12 student version.

Wald Test

Wald test is a parametric test for evaluating the significance of coefficients in the model. Wald test has a presumed hypothesis of coefficients being ineffective towards endogenous variable. Since the study aims to evaluate the effect of top three variables on Nifty hence the regression equation of Nifty as mentioned in the test was tested. The test result as displayed in Table 8 reveals that probability value exceeds 0.05, meaning failure to reject the presumed hypothesis. This implies that lag of FTSE, NASDAQ and NYSE do not affect Nifty.

Table 8

Wald Test
System : {%system}

Test Statistic	Value	df	Probability
Chi-square	10.37443	9	0.3210

* Presumed hypothesis is:
C(19)=C(20)=C(21)=C(22)=C(23)=C(24)=C(25)=C(26)=C(27)=0
The coefficients are for the equation DLNIFTY = C(19)*DLFTSE(-1) + C(20)*DLFTSE(-2) + C(21)*DLNASDAQ(-1) + C(22)*DLNASDAQ(-2) + C(23)*DLNIFTY(-1) + C(24)*DLNIFTY(-2) + C(25)*DLNYSE(-1) + C(26)*DLNYSE(-2) + C(27)

Source: Author's findings from test conducted in Eviews12 student version.

Variance Decomposition

Table 9 exhibits the variance decomposition results. The amount of variability in the endogenous variables due to exogenous variables is measured by variance decomposition. The results show that NIFTY is self-explanatory to the extent of 52.7% by its own lagged variable and over 5 lags it remains fairly constant. FTSE could explain 40.52% of the variance in NIFTY at first lag and it too remains fairly constant over a period of 5 lags. Almost negligible explanation to variance in NIFTY can be derived from NYSE and its lagged variables. Whereas, NASDAQ's contribution stands at about 7% over the period. Therefore, it can be concluded that lagged values of NIFTY and FTSE contribute to understanding the variance in NIFTY.

Table 9

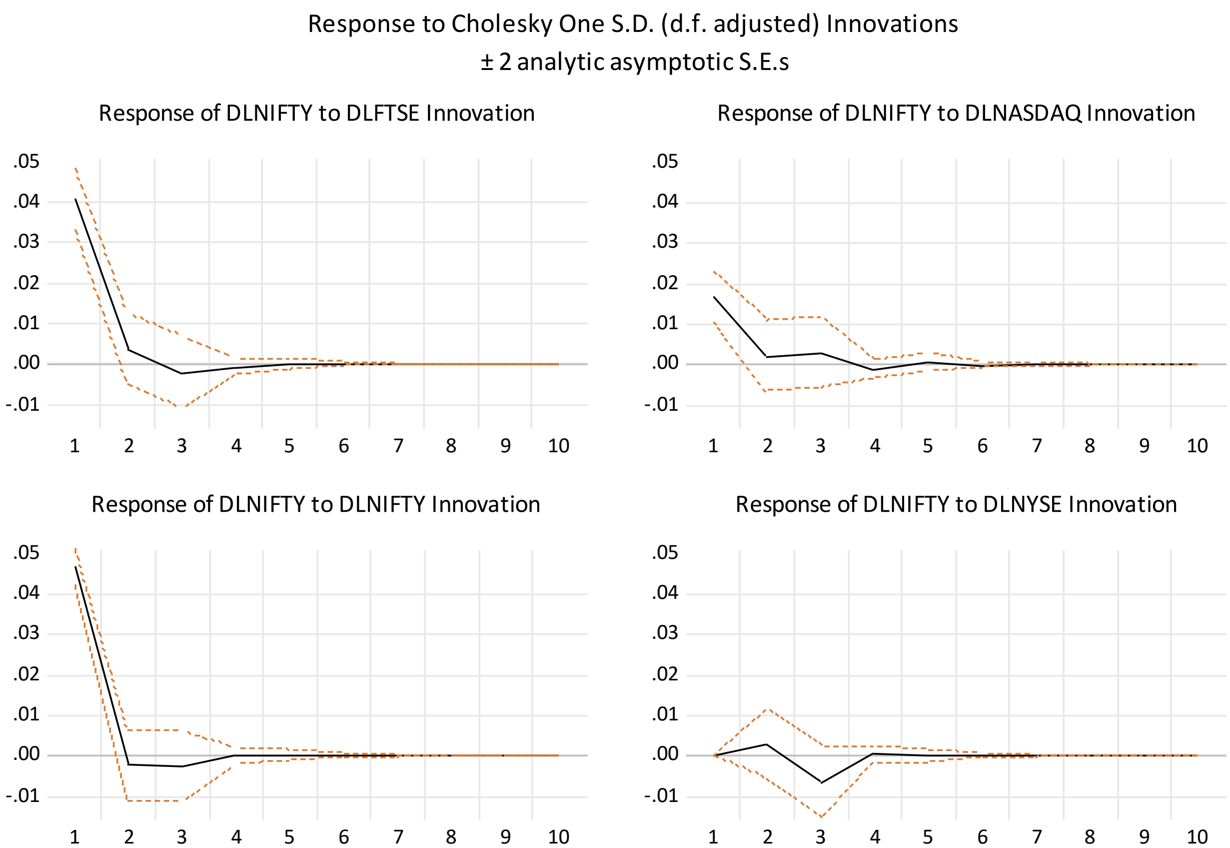
Variance Decomposition of DLNSE:					
Period	S.E.	DLFTSE	DLNASDAQ	DLNIFTY	DLNYSE
1	0.064076	40.52197	6.778977	52.69906	0.000000
2	0.064334	40.55818	6.826377	52.39887	0.216568
3	0.064825	40.06128	6.930573	51.78115	1.226993
4	0.064842	40.04768	6.968052	51.75285	1.231420
5	0.064845	40.04422	6.975584	51.74886	1.231336
Cholesky One S.D. (d.f. adjusted)					
Cholesky ordering:DLFTSE DLNASDAQ DLNIFTY DLNYSE					

Source: Author's findings from test conducted in Eviews12 student version.

Impulse Response Function

Corresponding to the observations in variance decomposition the impulse response function reveals the reaction of NIFTY to innovations in FTSE, NASDAQ and NYSE individually. Figure 1 demonstrates the responses of NIFTY to a unit standard deviation change in FTSE, NASDAQ and NYSE respectively. It is seen that there is a positive response from NIFTY in the first month from shocks in FTSE and NIFTY which dissipates by second month. Shock to NYSE fails to register a response in NIFTY and any shock to NASDAQ has almost minimal positive response in NIFTY.

Figure 1



Source: Author's findings from test conducted in Eviews12 student version.

Pair Wise Granger Causality Test

At the end to test for the short run causality, bivariate Granger Causality Test was conducted. This test helps to understand if the historical values of a time dependent variable can help in predicting the values of another time varying variable. Here, the objective is to understand whether the past values of FTSE, NASDAQ and NYSE impact NIFTY or gets impacted by its past values. The presumed hypothesis states an absence of Granger Causality within the variables subject to rejection at 5% level of significance. The test findings are displayed in table 10. It is observed that the probability values for all exceeds 0.05, meaning the impossibility to reject the presumed hypothesis, which means hypothesis H_{04}, H_{05}, H_{06} cannot be rejected. This reveals that there is no Granger

Causality between them and hence it is not helpful to use the past values of these variables to predict the other variables.

Table 10

Pairwise Granger Causality Tests
Sample 2005M01 2023M06
Lags:2

Null Hypothesis:	Obs	F-Statistic	Prob.
DLNIFTY does not Granger Cause DLFTSE	219	0.76867	0.4649
DLFTSE does not Granger Cause DLNSE		0.29397	0.7456
DLNIFTY does not Granger Cause DLNASDAQ	219	1.41437	0.2453
DLNASDAQ does not Granger Cause DLNIFTY		0.62337	0.5371
DLNYSE does not Granger Cause DLNIFTY	219	1.22382	0.2962
DLNIFTY does not Granger Cause DLNYSE		1.07354	0.3436

Source: Author's findings from test conducted in Eviews12 student version.

Conclusion

In conclusion, the analysis of the VAR model and its diagnostic tests reveals important insights into the relationship of Nifty with FTSE 100, NASDAQ, and NYSE. The variables Nifty, FTSE, NASDAQ, and NYSE were found to be stochastic at level, evidently signifying the presence of unit root. This problem was solved by differencing the variables, which made the time series stationary, making the vector autoregression model suitable for analysis. The absence of cointegration in the Johansen test suggests that the variables share no long-run equilibrium relationships with each other. Instead, short-run dynamics dominate their interactions, implying that the variables are more responsive to short-term shocks and adjustments. The lag order selection criteria indicate weak interactions in the short term among the variables, as a VAR model with 0 lags was deemed suitable. Furthermore, the lack of significant serial correlation in the residuals, as shown by the serial correlation LM test, validates the model's goodness of fit. The Wald test indicates that past values of FTSE, NASDAQ, and NYSE have no significant impact on Nifty's short-term behaviour. However, the variance decomposition analysis highlights Nifty's strong autocorrelation and significant contribution of FTSE in explaining its variation. The impulse response function illustrates Nifty's positive response to shocks in FTSE and NASDAQ in the short term, while shocks from NYSE and NASDAQ have minimal impact. Additionally, the bivariate Granger Causality tests reveal insignificant short-run causal relationships between the variables, suggesting that past values of FTSE, NASDAQ, and NYSE do not predict Nifty, and vice versa. In summary, no long-run cointegration or Granger causality exists, the short-term behaviour of Nifty is significantly influenced by its own past values and FTSE. These findings reveal that Nifty is independent of top 3 largest stock markets, which means that Nifty is largely insulated from major events in the top three largest stock markets. This is a positive sign for the Indian economy as lack of dependence from other capital market reveals that Indian capital market is stable enough. This may perhaps be the reason why foreign investors are gaining trust in the Indian capital market. And as share markets are barometers of Indian economy, this result indicates a stable economic progress of the country.

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