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Volatility Shocks and Stock Market Returns: An Econometric Investigation of the NIFTY 50

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Abstract
This article explores the effect of market volatility on NIFTY 50 returns with reference to the relationship between India VIX and NIFTY 50 index. The India VIX is India's key index, which shows the market's expectation of volatility over the near term, derived from the NIFTY.SP CNX-0100 Index Option prices. With the help of Johansen's co- integration probe we analyse the long-run equilibrium relationship between India VIX and NIFTY 50 returns. Moreover, the Granger causality test is used to investigate the direction of causality between market volatility and stock index returns. The objective of the research work is to find out if India VIX can be used as a robust predictor for NIFTY 50 movements or vice-versa by taking daily data. The findings of this empirical study are certainly expected to be invaluable in understanding the forecasting power for the stock market performance.

Keywords: NIFTY, Volatility, VIX Index, Granger Causality, Johanson's co-integration test.

1. Introduction
The volatility in the markets is a critical factor in influencing the sentiment of the investors and in making the decision to invest especially in the emerging economies like India. India Volatility Index (India VIX) is a measure of what is expected in the immediate future in regard to volatility, mainly it is the fear and uncertainty of the investor. The India VIX, which was launched at the National Stock Exchange (NSE) in 2008, measures the future volatility of the market based on the prices of NIFTY 50 options, and is therefore a forward-based indicator of market volatility. The volatility is one variable that has given a lot of concern in the world of finance because any understanding of volatility and stock market returns may help in gaining good insights on the areas of risk management and optimisation of portfolios (Whaley, 2000; Copeland and Copeland, 1999).

Various international markets have seen the application of volatility indices like the VIX often referred to as the fear gauge as a way of forecasting the trend of stock indexes and also give early signals of when the market is in increased risk (Giot, 2005). Earlier researchers, such as Black (1976) and French, Schwert and Stambaugh (1987) have pointed out the association between volatility and stock returns and established that, when the market is experiencing high volatility, it is likely that the stock prices will be falling. Nevertheless, the correlation between India VIX and NIFTY 50 index has not been thoroughly explored within the Indian market, which is where further research can be conducted.

The study intends to fill this gap by providing an empirical study on the effect of India VIX on NIFTY 50 returns on daily data. This research will analyze the long term equilibrium relationship between the returns of the India VIX and NIFTY 50 using the co-integration approach by Johansen as well as the directionality of causality between the returns and the volatility using Granger causality analysis (Granger, 1969; Johansen, 1991). With the adoption of these econometric methods, it is possible to perform a thorough examination of the dynamic processes between the two vital market signals.

The results of this study have great implications on the market participants such as investors, policymakers, and financial institutions. The presence of clear insight into the association of India VIX with the returns of NIFTY 50 will help investors to have a better risk management, portfolio allocation and forecast on market movement in the future. On the part of the policymakers, some findings of this study can help them make better decisions in relation to the regulation and stability of the markets especially when they are prone to high volatility like in cases of financial crises. Also, the research contributes to the current development of the literature on volatility-return relationship, which is more particularly applied to the Indian market due to the significance of the volatility in investment strategies (Mishra et al., 2010; Nousiainen, 2010). The gap in the empirical literature is that by filling this gap, the paper will increase the knowledge on the role of market volatility on stock returns in one of the largest emerging markets in the world.

2. Literature Review

Financial research has been a problematic area of study on the volatility of stock price and its connection with market returns. Early research by Black and Scholes (1973) on the prices of options brought the concept of volatility as a necessary element in the financial model, which would serve as the basis of later research on the dynamics of volatility. They have developed a model in the Black-Scholes option pricing model which has become a staple in the theory of finance because it shows how volatility is vital in option pricing and risk management. Merton (1973a) went ahead to add volatility to the intertemporal capital asset pricing model (ICAPM) which incorporated risk and returns across several periods. This was furthered in the theory of rational option pricing of Merton (1973b) who only explored more in the role of rational expectations in option pricing on the issue of volatility.

Black (1976) stressed on the dynamic aspect of the volatility which demonstrated that the volatility of stock prices is not a constant but varies throughout the time, usually in the reaction to the market conditions. This paper has demonstrated the significance of perceiving volatility as a variable that changes alongside the market and not being constant. This research was furthered by Schwert (1989, 1990) who examined the variation in stock market volatility over time especially during financial crisis. His contribution to the 1987 market crash presented a good understanding of the high volatilities in crises contributing to the market stress and volatility literature.

The volatility and causality have also been largely studied by the contributions of Granger (1969, 1988) who presented the idea of Granger causality to determine whether a time series can predict another or not. The approach has been very popular in financial studies to investigate the correlation between market volatility and stock returns, and provides a framework by which the predictive value of volatility indicators like the VIX and India VIX can be analyzed.
Following these initial research works, Hansen (1982) proposed the Generalized Method of Moments (GMM) that proved to be a significant instrument of the volatility model estimation. The approach permitted more elastic estimation of parameters in financial models, especially when large samples are involved and has since become a common practice in econometrics.

French, Schwert, and Stambaugh (1987) studied the relationship between stock expected returns and volatility and supported the notion that the high volatility is often accompanied by the falling prices of stocks. This negative correlation between volatility and stock returns has been commonly noted in the developed as well as the emerging markets. In the Indian context, Singh and Tripathi (2016) simulated stock market returns volatility and evidence that was given in the model shows that the negative relationship is true not only in India but also in other countries.
The cointegration concept brought about by Johansen (1991) has been used to study the long run equilibrium relationships between stock market indices and volatility values. His contribution on cointegration vectors has played a critical role in examining the relationship between market returns and the volatility index such as India VIX as observed in the literature by Chakrabarti and Kumar (2020). They empirically tested the high-frequency relationship of implied volatility of returns in the Indian market, which was added to the expanding body of literature concerning the volatility of emerging markets.

The volatility indices were also noted as future market sentiment indicators as demonstrated in the VIX, which is commonly known as the Investor Fear Gauge, that Whaley (2000) conducted. The idea has played a significant role in the comparison of the expectations of market risk by the investors on the volatility indices especially at times of uncertainty. VIX has been widely applied in Indian markets to predict the direction of future markets, as has been studied by Copeland and Copeland (1999), and very recently by Chakrabarti and Kumar (2020).

There are also a number of studies on the behavioral factors of volatility. Daniel, Hirshleifer and Subrahmanyam (1998) studied investor psychology and its influence on the market volatility. Their study of investor overreaction and underreaction has illuminated the aspects of behaviour that create volatility in the financial market. This can also be supported by the study conducted by Hong and Stein (1999), who came up with a single theory of momentum trading and overreaction, and these behaviors were attributed to the changes in volatility.

The role of volatility indices in the risk management and pricing of assets have been examined in the recent years. As an example, Pati, Rajib, and Barai (2019) have examined volatility index in determining the price of assets in the Indian stock market and have shown that volatility indices are useful in pricing assets and market risk management. Garg and Vipul (2015) examined the volatility risk premium in the prices of Indian options, and emphasized the need to incorporate volatility measures in the pricing formation of derivatives models.

The volatility studies in the Indian context have also been enhanced by the studies on external factors affecting market volatility. Parashar and Bangur (2024) tested the impact of the volatility of gold and crude oil on Nifty 50, and they found that commodity prices affect the volatility of the stock market in India significantly. However, in the same vein, Sarker (2024) evaluated the impact of the Indian gold price on the stock market volatility, which also gives additional confirmation of the interconnectedness between commodity markets and stock market action. All these studies lead to the knowledge of volatility in the financial markets, especially in an emerging market such as India. Combining the volatility metrics, behavioural variables and the external market effects in the financial models provides a simplified model of analyzing stock market returns and volatility.

Considering the Indian market scenario, the use of volatility indices such as the India VIX is instrumental in forecasting market behavior as well as risk management which is important both to investors as well as policymakers. The combination of the global and domestic variables and the sophisticated methods of econometrics gives a strong model of the complicated dependence between the volatility of the market and the stock returns.

3. Research Objectives

The primary objective of this study is to investigate the relationship between market volatility, as measured by the India Volatility Index (India VIX), and NIFTY 50 returns. Specifically, the research aims to explore the dynamics of volatility in the Indian stock market and how it influences the behavior of NIFTY 50, one of the country's key stock market indices.

This research aims to empirically examine the relationship between market volatility, as measured by the India Volatility Index (India VIX), and the returns of the NIFTY 50 index. The methodology consists of several steps, including data collection, pre-processing, and the application of advanced econometric techniques such as Johansen's co-integration test and Granger causality analysis. The data analysis and modeling will be conducted using R programming, an open-source statistical software that provides extensive tools for econometric modeling and data mining.

4. Data and Methodology

a. Data Collection

The study will use daily data for the India VIX and the NIFTY 50 index spanning from 1st April 2020 to 31st March 2024. Both datasets will be sourced from the official website of the National Stock Exchange (NSE) of India. The time period selected will ensure sufficient data points for robust analysis, and it will also encompass various phases of market volatility to provide a comprehensive view of the volatility-return relationship.

- India VIX: Daily closing values of India VIX will be collected. India VIX reflects the market's expectations of volatility over the next 30 days, derived from the prices of NIFTY 50 options.
- NIFTY 50 Returns: Daily closing prices of the NIFTY 50 index will be used to calculate the returns. The returns will be computed as the logarithmic difference of the index values.

b. Data Pre-Processing

Prior to analysis, the data will be checked for consistency, missing values, and outliers. Any missing values will be handled through interpolation or other relevant techniques to maintain data integrity. Both the India VIX and NIFTY 50 return series will be tested for stationarity using the Augmented Dickey- Fuller (ADF) test. This is crucial because the econometric techniques employed, such as co-integration and Granger causality, require that the data series be stationary or have certain co-integration properties.

c. Econometric Techniques

i. Johansen's Co-Integration Test

The Johansen co-integration test will be used to examine whether a long-term equilibrium relationship exists between India VIX and NIFTY 50 returns. Co- integration analysis is particularly useful when two or more time series are non- stationary but exhibit a stable long-term relationship.

Steps for Johansen's co-integration test:

- Determine Lag Length: The appropriate lag length for the co-integration test will be selected using criteria such as the Akaike Information Criterion (AIC) or the Schwarz Information Criterion (SIC).
- Estimate Co-Integration: The co-integration relationship will be tested under the hypothesis that no co-integrating relationship exists, and the number of co- integrating vectors will be identified using the trace statistic and the maximum eigenvalue test (Johansen, 1991).

The co-integration test results will indicate whether a long-term relationship exists between market volatility, as captured by India VIX, and NIFTY 50 returns.

ii. Granger Causality Analysis

To investigate the direction of causality between India VIX and NIFTY 50 returns, Granger causality tests will be performed. Granger causality analysis helps determine whether past values of one time series can be used to predict future values of another time series (Granger, 1969).
The following hypotheses will be tested:

- Null Hypothesis 1 (H0): India VIX does not Granger-cause NIFTY 50 returns.
- Null Hypothesis 2 (H0): NIFTY 50 returns do not Granger-cause India VIX.

If the null hypothesis is rejected, it indicates a unidirectional or bidirectional causality between the two variables. The results of the Granger causality tests will provide insights into whether changes in India VIX predict NIFTY 50 returns or vice versa.

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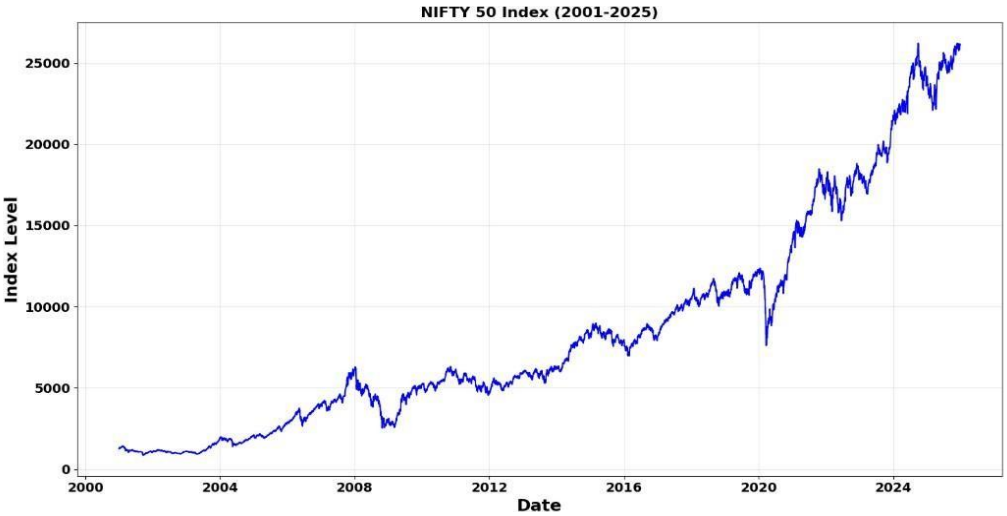


Figure 1.1 shows the evolution of the Nifty 50 index over the period 2001–2025, revealing a pronounced long-run upward trajectory punctuated by two major crisis- induced drawdowns. Starting from a level of about 1,254 points in 2001, the index rises to approximately 26,142 points by 2025, implying a cumulative price return of nearly 1,984 percent and underscoring the strong secular expansion of the Indian equity market over the sample horizon. The path, however, is far from smooth. The first large break in the trend occurs during the Global Financial Crisis (GFC) of 2008– 2009, where the index falls sharply from its pre-crisis peak above 6,000 points to a trough near the 2,500–2,700 range, wiping out several years of prior gains and indicating a substantial destruction of market capitalization within a short span. A second, even more abrupt collapse is observed around early 2020 during the outbreak of the Covid-19 pandemic, when the index drops from levels around 12,000 to below 8,000, reflecting heightened uncertainty, liquidity stress and a rapid reassessment of growth expectations. In both episodes, the subsequent recoveries are swift and eventually push the index to successive all-time highs, suggesting that while systemic crises generate deep but temporary deviations from the long-term trend, they are followed by phases of accelerated growth as risk appetite returns and macroeconomic conditions stabilize.

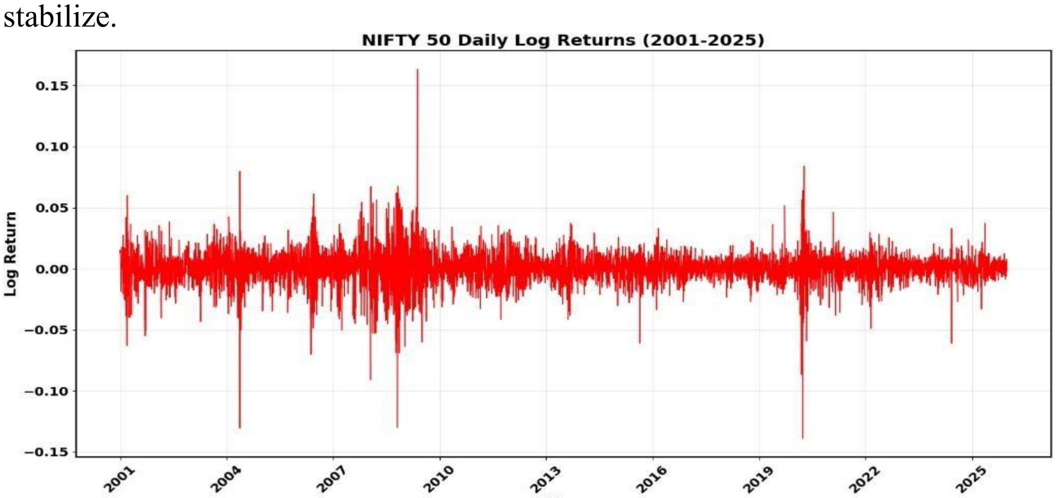
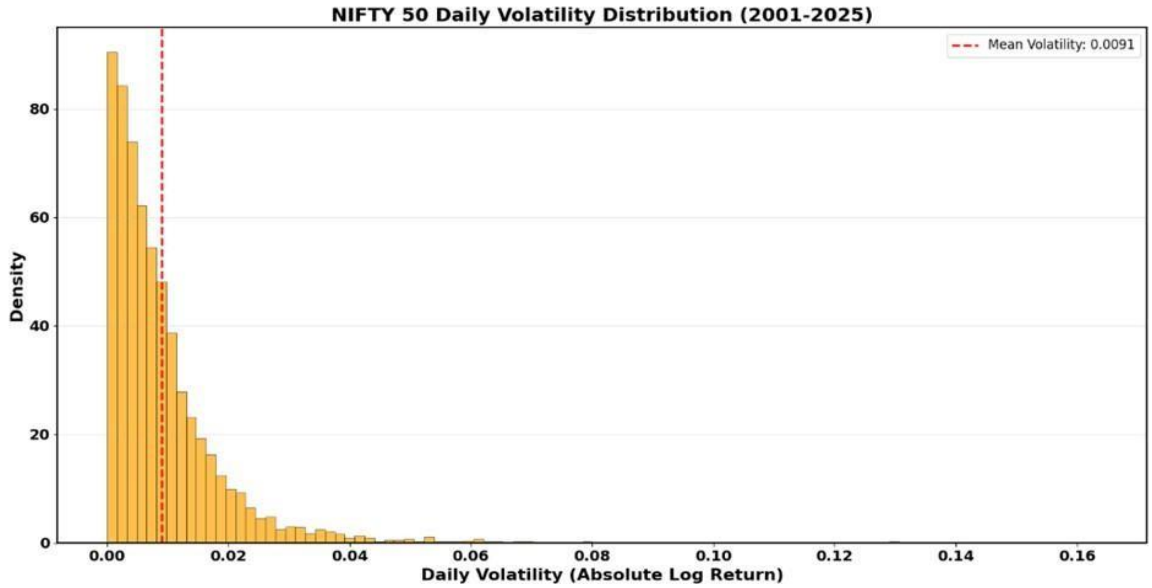


Figure 1.2 Logarithm Daily Returns of (2001-2005)

However, the plot also reveals several episodes of extreme positive and negative returns, which appear as vertical spikes and are particularly pronounced during the Global Financial Crisis (2008–2009) and the Covid-19 crash in early 2020, when daily log returns reach values below



−0.12 and above 0.15 in absolute terms.

Figure 1.3 NIFTY 50 Daily Volatility Distribution (2001-2025)

The mean daily volatility of about 0.0091 exceeds the median of roughly 0.0064, confirming that relatively infrequent high-volatility days pull the average to the right of the central mass of the distribution. The standard deviation of approximately 0.0099 indicates substantial dispersion around this mean, while the maximum observed volatility of nearly 0.1633 reflects crisis-period moves when the index lost or gained more than 16 per cent in a single day, as occurred during the Global Financial Crisis and the Covid-19 shock.

The entire econometric analysis will be performed using R programming, leveraging its packages such as ‘t-series’, ‘vars’, and ‘urca’ for time series analysis. R provides powerful functions for running stationarity tests, co- integration analysis, and causality tests, as well as for visualizing the results.

The results of the co-integration and Granger causality tests will be interpreted to assess both the short-term and long-term relationships between India VIX and NIFTY 50 returns. Based on the findings, the paper will provide empirical insights into how market volatility impacts stock market performance in the Indian context. This analysis will also help determine the predictive power of India VIX for forecasting NIFTY 50 returns.

This methodology provides a comprehensive approach to analyzing the relationship between India VIX and NIFTY 50 returns. The use of R programming for data mining and statistical analysis ensures a systematic and reproducible approach to investigating the volatility-return relationship. By employing Johansen’s co-integration and Granger causality tests, this study aims to offer valuable insights into how market volatility influences stock market returns in India.

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5. Empirical Result

The Augmented Dickey-Fuller (ADF) test is a critical econometric tool used in time series analysis to check for the presence of a unit root, which indicates whether a time series is stationary.

Any subsequent analysis, such as the Johansen cointegration test or Vector Error Correction Model (VECM), might produce misleading results without first confirming stationarity through the ADF test. Stationary data is necessary to avoid false relationships that may arise purely due to shared trends in the data.

Table 1: ADF test results for NIFTY returns.

Coefficients	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	63.296326	25.678065	2.465	0.0139
lagged_data	-0.002988	0.001529	-1.955	0.0509
diff_lag_data	0.026102	0.031761	0.822	0.4114

The ADF test results for NIFTY returns are presented in the table above.

The intercept term in the ADF test represents the mean of the NIFTY returns over the testing period. The estimated value of 63.296326 suggests a relatively high mean value for NIFTY returns during the sample period. The p-value (0.0139) associated with the intercept indicates statistical significance at the 5% level ($p < 0.05$). This means that the intercept is significantly different from zero, suggesting that the NIFTY returns exhibit a non-zero mean.

The coefficient of the lagged NIFTY returns in the ADF test is crucial because it tells us whether there is a unit root in the time series. The estimate of -0.002988 is negative, which suggests that the series is mean-reverting. In other words, it provides evidence against the presence of a unit root. The t-value (- 1.955) and the p-value (0.0509) indicate marginal statistical significance at the 5% level.

The first difference term represents the effect of changes in past NIFTY returns on current returns. The estimated coefficient of 0.026102 indicates that changes in the past NIFTY returns have a small positive effect on current returns. The p-value (0.4114) is much greater than 0.05, indicating that this term is not statistically significant. Therefore, changes in the lagged returns do not have a significant effect on the NIFTY 50 returns.

Table 2: ADF test results for VIX returns.

Coefficients	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.497627	0.097007	5.130	0.00000034909
lagged_data	-0.029755	0.005002	-5.949	0.00000000375
diff_lag_data	-0.085645	0.030894	-2.772	0.00567

The intercept represents the mean of the VIX returns over the testing period. The estimated value of 0.497627 suggests that, on average, VIX returns have a positive value over time. The t-value

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and the p-value indicate that the intercept is statistically significant, meaning the VIX returns have a non-zero mean during the period analyzed.

The coefficient of the lagged VIX returns is negative, which is a strong indicator that the VIX series is stationary. The t-value -5.949 is highly significant, and the p-value 0.0000000375 is well below the 0.05 threshold, indicating that we can reject the null hypothesis of the ADF test. This strongly suggests that the India VIX series does not contain a unit root and is stationary.

Table 3: Johansen's Cointegration test results

Hypothesized Number of Cointegrating Equations	Eigen Value	Trace Statistics	Critical Value At 5% level	Maximum Eigen Statistics	Critical Value at 5%
None	0.0411407	2.045766	8.18	2.045766	14.90
At Most 1	0.0020643	43.636616	17.95	41.590850	8.18

Johansen's cointegration test is a vital econometric tool used to determine whether a long- term equilibrium relationship exists between the variables under study: the NIFTY 50 Index and the India VIX. Cointegration is critical because, even if both time series are non- stationary, they can move together over time, implying that there is a long-term relationship between them.
The eigenvalue measures the strength of the relationship between the variables. The higher the eigenvalue, the stronger the relationship. For the hypothesis of no cointegration, the eigenvalue is 0.0411407, and for at most one cointegrating equation, the eigenvalue is 0.0020643. A lower eigenvalue typically indicates a weaker relationship. In this case, the eigenvalue is much smaller for the 'At Most 1' scenario, suggesting a relatively weaker second cointegration equation if it exists.

For the hypothesis of no cointegration, the maximum eigenvalue statistic is 2.045766, which is lower than the critical value of 14.90. This implies that we cannot reject the null hypothesis of no cointegration, meaning there is no significant evidence of cointegration at this level. For the hypothesis of at most one cointegrating equation, the maximum eigenvalue statistic is 41.590850, which is higher than the critical value of 8.18. This indicates that there is strong evidence of one cointegrating equation between the NIFTY 50 and India VIX returns.

Johansen's Cointegration Test suggests that there is no significant long-term equilibrium relationship between NIFTY 50 returns and India VIX when assuming no cointegration and there is significant evidence to support the existence of one cointegrating equation between NIFTY 50 returns and India VIX which indicates that these two variables move together in the long term. Even though they may drift apart in the short term, there is an underlying equilibrium relationship pulling them back together over time. It also indicates that changes in market volatility (VIX) are closely related to stock market returns (NIFTY 50) in the long run. Thus, market volatility can be used as an indicator for predicting future stock market movements.

Table 4: Normalized Cointegration Vectors

	Ect1

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Vix l2	1.000
Nifty 12	1081.151

The value for VIX.l2 is set to 1.000, which means that the India VIX is used as the baseline in this cointegration relationship. The value for NIFTY l2 is 1081.151, which implies that for every unit change in the VIX, the NIFTY returns move by a factor of 1081.151 in the opposite direction to maintain the long-term equilibrium.

The presence of a cointegrating vector indicates that the NIFTY 50 and India VIX share a long-term equilibrium relationship. Even though these two variables may deviate in the short run, they are bound by a common long-term trend. A significant rise in India VIX, which indicates increased market uncertainty, is likely to be associated with a sharp decline in NIFTY 50 returns. The large coefficient of 1081.151 for NIFTY 50 suggests that the NIFTY index is highly sensitive to changes in market volatility. Small movements in VIX can result in substantial adjustments in NIFTY 50 returns.

This result supports the hypothesis that market volatility has a significant impact on stock returns, aligning with the theoretical expectation that higher volatility leads to lower stock market performance.

Table 5: VECM test results

Variable	Vix	Nifty
Error Correction Terms	1.0000000	2.7124796
Deterministic	0.0011231	-0.0085453
Lagged Differences	-0.0185506	-0.0101639

The error correction term represents how quickly the dependent variables VIX and NIFTY respond to the long-term disequilibrium. For VIX the ECT coefficient is normalized to 1.000000. This means that the India VIX fully adjusts to deviations from the long-term equilibrium relationship with NIFTY 50. For NIFTY the ECT coefficient is 2.7124796, which is significantly larger than 1. This suggests that NIFTY 50 returns adjust relatively slowly to deviations from the long-run equilibrium with the India VIX. The negative coefficients for lagged differences indicate that both VIX and NIFTY show mean-reverting behavior in the short term. Increases in volatility or drops in NIFTY 50 tend to revert toward their equilibrium after a short period, though the magnitude of the effect is relatively small. The results of the VECM confirm that while NIFTY 50 and VIX are closely related in the long term, their short- term dynamics and responses to disequilibrium differ significantly, with the stock market NIFTY 50 being more stagnant in response to volatility shocks than the volatility index itself.

Table 6: Granger Causality Test Results

Null Hypothesis	F Statistic	Probability	Decision
VIX does not Granger Cause Nifty	0.5531099	0.7941692	Reject
Nifty does not Granger Cause VIX	2.7968320	0.0069346	Accept

The results indicate that market volatility, as measured by India VIX, does not predict future NIFTY 50 returns. This could imply that volatility, in itself, is a reactionary measure that adjusts to market movements but does not act as a leading indicator for stock prices. On the other hand, NIFTY 50 returns have a significant predictive influence on VIX. This finding suggests that changes in stock market returns drive market volatility. When NIFTY experiences significant movements either positive or negative, volatility tends to rise as investors react to these changes.
Granger causality test suggests that stock market returns can lead to changes in market volatility, rather than volatility leading to stock market changes. The results of the Granger causality test provide an important insight into the dynamic relationship between market volatility and stock returns:

- NIFTY 50 returns Granger cause India VIX, meaning that stock market returns can help predict future changes in market volatility.
- India VIX does not Granger cause NIFTY 50 returns, suggesting that market volatility does not significantly predict future stock market performance.

This finding highlights the importance of monitoring stock market returns to anticipate future volatility in the Indian market.

6. Conclusion

The research objective of the study was to examine the connection between the market volatility, in terms of India VIX and stock market returns in terms of NIFTY 50 Index. We analyzed the short-run and long-run relationship between these two key variables in the Indian stock market using the different econometric models and statistics that included, the Augmented Dickey-Fuller (ADF) test, Johansen cointegration test, Vector Error Correction Model (VECM) as well as the Granger Causality Test.

This paper validates the presence of a strong long-term correlation between the market volatility (India VIX) and returns of the NIFTY 50, in which volatility affects the performance of the stock market adversely. Although volatility reacts to fluctuations in the stock market it does not cause stock market movements, which supports the notion that volatility is a major reflection of uncertainty in the market. In general, this study will have significant implications on the dynamics of market volatility and stock returns in India and the study will bring value to investors, policymakers and market analysts.

The research has shown how crucial the performance of the stock market is in the dynamics of market volatility and presented a very useful framework in forecasting future market performance by examining the short and long term correlation between these two variables.

7. Limitations and Future Research Areas:

Although the given work contains useful data about the correlation between the returns of NIFTY 50 and India VIX, there are certain limitations that should be explored:

- Sample Period: The findings are founded on past data and dynamic of volatility and returns may change as time goes by, particularly in extreme time market conditions. Future research can take into account how external shocks affect the volatility-returns relationship.

- Other Factors: There are other factors that may affect the relationship between market volatility and stock returns e.g. global market indices, and macroeconomic factors e.g. interest rates, and inflation. The inclusion of these variables may help gain a better insight into the movements in the market.

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