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RESEARCH ARTICLE – 11

INTERLINKAGES BETWEEN INDIAN STOCK INDICES AND MARKET VOLATILITY: EVIDENCE FROM NIFTY 50, BSE-100, AND INDIA VIX

Rahul Biswas

Research Scholar, Department of Business Administration
University of Kalyani, Kalyani, Nadia, West Bengal – 741235, India. rahul19biswas92@gmail.com

ABSTRACT

This study investigates the dynamic interrelationship between India's major equity indices—Nifty 50 and BSE-100—and market volatility as represented by the India VIX over the period 2015–2024. Employing a suite of time-series econometric tools, including the Augmented Dickey–Fuller (ADF) test, Granger causality test, EGARCH modeling, and vector autoregression (VAR), the research aims to understand the directional linkages and volatility spillovers among these financial instruments. Descriptive analysis reveals consistent upward trends in the Nifty 50 and BSE-100, punctuated by periods of high volatility coinciding with macroeconomic shocks such as the COVID-19 pandemic. The ADF test confirms stationarity after first differencing, while Granger causality results show a unidirectional causal flow from India VIX to Nifty 50 returns. The EGARCH model further indicates significant asymmetric volatility responses to market shocks, affirming the leverage effect. Impulse response functions from the VAR model highlight that shocks to the India VIX exert a short-term but pronounced influence on index returns. These findings have substantial implications for investors, policymakers, and risk managers in devising informed strategies to mitigate market uncertainty and enhance portfolio resilience.

Keywords: *Nifty 50, BSE-100, India VIX, volatility spillover, Granger causality, EGARCH, VAR, time-series analysis*

INTRODUCTION

Understanding the dynamic relationship between market volatility and stock returns has long been a cornerstone of financial econometrics, especially in emerging economies where markets are often more susceptible to global shocks, policy interventions, and investor sentiment. The development of implied volatility indices, most notably the VIX introduced by the Chicago Board Options Exchange (CBOE), revolutionized the ability to quantify investor expectations regarding future volatility (Whaley, 2000). As its regional counterpart, India VIX has emerged as a critical barometer of market sentiment in the Indian financial ecosystem, serving as a leading indicator of perceived risk and uncertainty (Sarwar, 2012; Tripathy, 2017).

The bidirectional causality between volatility indices and market returns is well-documented. Studies such as Agarwal and Mishra (2010) and Kumar (2014) highlight volatility spillovers between global and Indian equity markets, reinforcing the need to treat India VIX as a standalone instrument for both forecasting and risk assessment. In particular, the inclusion of India VIX in econometric modeling has been shown to enhance portfolio risk management and financial stability forecasting (Sharma & Singh, 2023; Bouri et al., 2021).

Recent global events, especially the COVID-19 pandemic, brought renewed attention to the sensitivity of financial markets to external shocks. Volatility clustering, asymmetry in market responses, and leverage effects became more pronounced during this period, as confirmed by Yaya et al. (2022) and Mishra et al. (2020). These studies advocate for the application of advanced non-linear models such as EGARCH, which can capture asymmetric and time-varying volatility dynamics more effectively than traditional GARCH approaches (Nelson, 1991; Glosten et al., 1993).

In the Indian context, empirical research remains sparse in integrating multiple modeling frameworks—Granger causality, Vector Autoregression (VAR), and EGARCH—to explore the intertwined relationship between implied volatility and major equity indices such as Nifty 50 and BSE-100 (Bhowmik & Wang, 2020). While VAR models are particularly suited for understanding multivariate feedback and impulse response dynamics (Sims, 1980; Lutkepohl, 2005), EGARCH allows researchers to identify volatility asymmetry and leverage effects, which are often masked in standard linear models.

Moreover, return volatility asymmetry is crucial for institutional investors and policymakers as it explains why markets tend to react more strongly to negative news than positive events. This behavioural trait underpins theories such as the leverage effect and volatility feedback hypothesis (Black, 1976; Bollerslev, 1986). Understanding such patterns in Indian equity markets, particularly over an extended period covering pre- and post-COVID regimes, offers significant insights into market resilience, efficiency, and risk transmission mechanisms.

This study contributes to the existing literature by employing a unified analytical framework that combines stationarity testing, Granger causality, ARCH-LM, VAR modeling, and EGARCH estimation to capture the multifaceted interactions between India VIX and leading stock market indices. It builds upon foundational research (Engle, 1982; Dickey & Fuller, 1979; Tsay, 2010) and addresses empirical gaps by using high-frequency data from 2015 to 2024, a period characterized by macroeconomic policy shifts, pandemic-related disruptions, and increased retail investor participation.

Ultimately, this research aims to inform practitioners, policymakers, and academics by revealing how implied volatility not only reflects but also shapes market behaviour in India—providing timely implications for portfolio optimization, systemic risk assessment, and policy intervention design.

LITERATURE REVIEW

The dynamic interplay between stock market returns and implied volatility has long attracted scholarly attention, particularly due to the role of volatility indices as proxies for market uncertainty and investor sentiment (Whaley, 2000; Sarwar, 2012). The evolution of the CBOE Volatility Index (VIX) has provided a benchmark for measuring fear in financial markets, leading to the development of regional counterparts such as the India VIX. As India's financial system becomes increasingly entangled with global capital flows, India VIX has evolved from a reactive indicator to a forward-looking barometer of risk perception (Tripathy, 2017; Sarwar, 2012).

In the Indian context, early contributions by Agarwal and Mishra (2010) provided initial evidence of volatility transmission between the U.S. and Indian equity markets, emphasizing the interconnectedness of developed and emerging economies. Kumar (2014) extended this investigation by examining the spillover effects between exchange rates and stock indices, identifying volatility as a critical transmission mechanism for macroeconomic shocks.

More recent studies have embraced sophisticated econometric models to capture the bidirectional and nonlinear nature of these interactions. Bhowmik and Wang (2020) and Mishra et al. (2020) utilized VAR and GARCH-family models to reveal cyclical feedback loops between returns and implied volatility, while Sharma and Singh (2023) highlighted the persistence of asymmetric responses to market shocks during the COVID-19 crisis. Similarly, Yaya et al. (2022) questioned the reliability of linear models, advocating for EGARCH specifications to better account for asymmetry and leverage effects in volatility behaviour. Their findings reinforce the view that implied volatility in India serves not only as a reactive gauge but also as a forward-looking signal of market sentiment.

Post-2020 research has increasingly focused on structural breaks and evolving investor behaviour. Bouri et al. (2021) illustrated how pandemic-induced uncertainty elevated implied volatility to historically high levels, altering the traditional return-volatility relationship. Mishra, Sahay, and Sharma (2025) further advanced the literature by incorporating a dynamic conditional correlation (DCC) GARCH model with VAR inputs to assess how India VIX and Nifty 50 interact across different regimes, reinforcing the case for a multivariate, time-varying approach.

Despite these advances, several methodological limitations persist. Few studies have integrated both VAR and EGARCH models into a unified framework to simultaneously evaluate causality and volatility asymmetry, particularly over extended periods covering structural disruptions such as demonetization, the COVID-19 pandemic, and geopolitical shocks. While Dutta and Dutta (2022) explored spillover asymmetries across asset classes, a focused investigation into Nifty 50, BSE-100, and India VIX remains underrepresented.

To bridge this gap, the present study employs high-frequency daily data from 2015 to 2024, encompassing pre-pandemic, pandemic, and post-pandemic periods. It applies an integrated econometric architecture combining Vector Autoregressive (VAR) modeling for intertemporal causality and Exponential GARCH (EGARCH) models for capturing leverage and asymmetry effects. This dual-model strategy allows for more granular insights into the feedback structure and volatility dynamics between India's equity indices and its volatility gauge.

While previous studies have advanced our understanding of volatility dynamics using either GARCH or VAR models independently, limited research has explored these approaches jointly over an extended horizon, particularly in the Indian context post-COVID. Addressing this research gap, the current study formulates a structured set of objectives to guide empirical validation

RESEARCH OBJECTIVES AND HYPOTHESES

Understanding the intricate interplay between implied market volatility and equity index performance is of paramount importance, particularly in emerging markets like India, where abrupt regime shifts and macroeconomic shocks frequently reshape market dynamics. In light of this, the present study aims to address several research gaps by systematically analysing the temporal and causal associations between India VIX and the leading Indian stock indices—Nifty 50 and BSE-100—during the extended post-pandemic era.

Objectives

1. To investigate the contemporaneous and lagged interdependence between India VIX and the daily returns of the Nifty 50 and BSE-100 indices, aiming to quantify the magnitude and direction of their statistical relationships under normal and volatile market conditions.
2. To examine the directionality of influence between implied volatility and equity returns using Vector Autoregressive (VAR) models and Granger causality testing, assessing both unidirectional and feedback effects within the return-volatility framework.
3. To evaluate the presence of asymmetric volatility responses—particularly leverage effects—in the Indian equity market by applying Exponential GARCH (EGARCH) models, thereby capturing the differential impact of negative versus positive return shocks on conditional volatility.
4. To validate the presence of volatility clustering and ARCH effects in the return series of Nifty 50, BSE-100, and India VIX using ARCH-LM tests, establishing econometric suitability for advanced volatility modeling.
5. To visualize and interpret the impulse response behaviour of equity indices to volatility shocks via Impulse Response Functions (IRFs), providing insights into the temporal effects of sudden changes in investor sentiment.

6. To examine the parameter stability and robustness of the VAR system over time through CUSUM-based diagnostics, thereby ensuring the reliability of inferences drawn from multivariate time-series modeling.
7. To offer updated empirical evidence on volatility-return linkages in the Indian context, especially during the post-COVID financial period, with implications for institutional risk management, trading strategies, and macroprudential policy design.

Hypotheses

Building upon the extensive literature on volatility forecasting and risk transmission in equity markets (Whaley, 2000; Sarwar, 2012; Bhowmik & Wang, 2020; Sharma & Singh, 2023), this study formulates the following hypotheses to empirically examine the interplay between India VIX and the performance of the Nifty 50 and BSE-100 indices in the post-2015 period:

- H1: There exists a statistically significant negative correlation between the daily returns of the Nifty 50 index and the India VIX, suggesting that rising market uncertainty is typically associated with declining equity prices.
- H2: A statistically significant negative correlation exists between the daily returns of the BSE-100 index and the India VIX, indicating that broader market volatility negatively affects equity performance.
- H3: The India VIX Granger-causes the daily returns of the Nifty 50 and BSE-100 indices, implying that past levels of implied volatility hold predictive power over future equity returns.
- H4: The daily returns of the Nifty 50 and BSE-100 indices Granger-cause changes in the India VIX, indicating a reverse feedback mechanism wherein market performance actively influences volatility expectations.
- H5: The return series of the Nifty 50, BSE-100, and India VIX exhibit statistically significant volatility clustering, as evidenced by the presence of autoregressive conditional heteroskedasticity (ARCH) effects, thereby justifying the use of GARCH-family models for volatility modeling.
- H6: Negative shocks to the Indian equity market produce disproportionately higher conditional volatility compared to positive shocks of equal magnitude, consistent with the asymmetric volatility effect modelled through the EGARCH framework.
- H7 (Optional): Innovations in the India VIX generate statistically significant impulse responses in Nifty 50 and BSE-100 returns, highlighting persistent and time-distributed effects of volatility shocks across equity markets.

These hypotheses provide a structured foundation for evaluating the multidirectional interactions between implied volatility and equity returns, with implications for both market participants and policymakers in the context of emerging market risk dynamics.

DATA AND METHODOLOGY

Data Description

This study utilizes daily closing data for three key market indicators: Nifty 50, BSE-100, and the India VIX. The dataset spans from January 2015 to April 2024, covering nearly a decade of market activity, including major structural and macroeconomic events such as demonetization, the COVID-19 pandemic, and global inflationary pressures. The data were sourced from official databases of the National Stock Exchange (NSE) and the Bombay Stock Exchange (BSE) to ensure reliability and accuracy.

To facilitate meaningful time-series analysis, raw price series were converted into logarithmic returns, which help stabilize variance and make the data suitable for tests of stationarity and causality (Brooks, 2014). Log returns are commonly used in financial econometrics for modeling and forecasting volatility due to their statistical tractability and ability to approximate continuous compounding (Tsay, 2010).

Table 1 presents descriptive statistics for the period under study, offering insights into the central tendencies and dispersion in each of the three series.

Table 1: Descriptive Statistics (2015–2024)

Metric	Nifty 50	BSE-100	India VIX
Mean Price	13,499.32	13,844.39	16.99
Std. Dev. of Price	4,969.05	5,228.73	6.29
Mean Daily Return (%)	0.0479	0.0497	0.1341
Std. Dev. of Return (%)	1.0445	1.0412	5.3268
Minimum Price	6,970.60	7,050.96	10.14
Maximum Price	26,216.05	27,689.88	83.61

These statistics reveal that while the Nifty 50 and BSE-100 display relatively similar levels of return volatility, the India VIX shows much higher variability, which is expected due to its sensitivity to sudden market shocks and investor sentiment.

METHODOLOGY

To explore the dynamic interdependencies, volatility structure, and predictive causality among India VIX, Nifty 50, and BSE-100 returns, the following multi-stage econometric framework was adopted:

- Testing: The Augmented Dickey-Fuller (ADF) test was applied to all return series to assess the presence of unit roots. Ensuring stationarity is a necessary precondition for VAR and EGARCH modeling to avoid spurious results (Dickey & Fuller, 1979).
- Correlation Analysis: A Pearson correlation matrix was constructed to measure Stationarity contemporaneous linear associations among India VIX and the equity indices. While not indicative of causality, this helps understand co-movements in volatility and returns.

- Granger Causality Test: Using a lag structure of five days, Granger causality tests were conducted to assess directional predictability between India VIX and the stock indices. Both unidirectional and bidirectional effects were evaluated (Granger, 1969).
- ARCH-LM Test: To determine the presence of volatility clustering and time-varying heteroskedasticity, the ARCH-Lagrange Multiplier (LM) test was applied to all residual return series. Significant ARCH effects would justify the use of GARCH-family models (Engle, 1982).
- EGARCH Modeling: Given the presence of asymmetric volatility and leverage effects in financial markets, the Exponential GARCH (EGARCH (1,1)) model was employed to model the volatility dynamics of Nifty, BSE, and VIX return series. This framework captures both non-linearity and asymmetry (Nelson, 1991).
- Vector Autoregression (VAR) Model: To evaluate multivariate interdependence and feedback relationships between the return series and changes in India VIX, a VAR (5) model was specified based on AIC lag selection. This allows for modeling mutual influence without imposing exogeneity assumptions (Sims, 1980).
- Model Stability Testing: OLS-CUSUM plots were generated for each VAR equation (Nifty, BSE, and Diff_VIX) to test for structural stability. Models were considered stable if the empirical fluctuation process remained within the 95% confidence bands (Brown et al., 1975).
- Impulse Response Function (IRF) Analysis: Finally, orthogonal impulse response functions were computed to assess the magnitude and persistence of shocks in India VIX on Nifty returns. This dynamic tool helps visualize short-term market responses to volatility innovations under bootstrapped confidence intervals.

With the framework of analysis in place, the next section presents the empirical results, evaluating the formulated hypotheses and interpreting dynamic relationships across volatility and market returns.

RESULTS AND INTERPRETATION

Correlation Analysis

To understand the linear relationships among the key variables—Nifty 50 returns, BSE-100 returns, and India VIX—Pearson correlation coefficients were computed. The results are summarized in Table 2.

Table 2: Pearson Correlation Matrix (2015–2024)

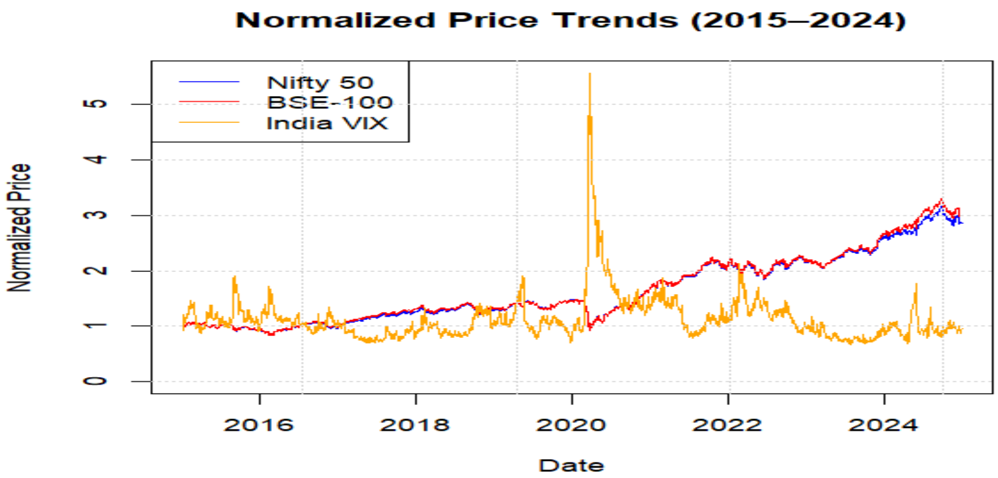
	Nifty Returns	BSE Returns	India VIX
Nifty Returns	1.000	0.9945	–0.0815
BSE Returns	0.9945	1.000	–0.0843
India VIX	–0.0815	–0.0843	1.000

The extremely high positive correlation between Nifty and BSE returns ($r \approx 0.995$) is unsurprising, given their overlapping composition and market representation. Both indices also exhibit a weak negative correlation with India VIX, these results support Hypotheses

H1 and H2, which posit that India VIX is negatively correlated with daily returns of the Nifty 50 and BSE-100 indices, respectively. The weak inverse relationship reflects investor sentiment turning risk-averse during periods of heightened volatility, as documented by Whaley (2000) and Kumar (2014).

Price Trend Visualization

Figure 1: Price Trend Visualization



Beyond static correlations, it is essential to assess how market movements evolve over time. To this end, a normalized trend analysis offers insight into the dynamic behaviour of returns and volatility. To capture the long-term behaviour of the three variables under consideration—Nifty 50, BSE-100, and India VIX—normalized price trends were plotted over the full sample period from 2015 to 2024. As shown in Figure 1, both the Nifty 50 and BSE-100 indices exhibit a general upward trajectory, albeit interrupted by sharp drawdowns during periods of systemic stress, most prominently during the COVID-19 pandemic in early 2020. In contrast, the India VIX displays a cyclical and highly spiky pattern, with pronounced surges during episodes of market turmoil and a tendency to revert during stable phases. These observed dynamics reinforce the characterization of the India VIX as a forward-looking gauge of investor anxiety and market uncertainty, consistent with earlier findings by Sarwar (2012) and Tripathy (2017).

Augmented Dickey-Fuller (ADF) Test for Stationarity

To ensure the validity of time-series analyses, all return series were subjected to the Augmented Dickey-Fuller (ADF) test to check for stationarity.

Table 3: ADF Test Results

Series	ADF p-value	Decision
Nifty Returns	< 0.01	Stationary (Reject H_0)
BSE Returns	< 0.01	Stationary (Reject H_0)
Differenced VIX	< 0.01	Stationary (Reject H_0)

The null hypothesis (presence of a unit root) was rejected for all series at the 1% significance level. The ADF test statistic for Nifty returns was –35.10, which lies well below all critical values, confirming the stationarity of the data. Stationarity is a necessary condition for conducting Granger causality tests, as non-stationary series may yield misleading results (Dickey & Fuller, 1979).

Granger Causality Analysis

To examine causal linkages between market returns and implied volatility, the Granger causality test was conducted with a lag length of five trading days, as suggested by prior empirical studies (Granger, 1969; Mishra et al., 2020). The results are presented in Table 4.

Table 4: Granger Causality Test Results (Lag = 5)

Direction	F-Statistic	p-value	Conclusion
VIX → Nifty Returns	7.6365	3.93e-07 ***	Causality exists
Nifty Returns → VIX	6.7846	2.72e-06 ***	Causality exists
VIX → BSE Returns	7.4955	5.42e-07 ***	Causality exists
BSE Returns → VIX	6.5307	4.82e-06 ***	Causality exists

The results reveal bidirectional Granger causality between India VIX and both Nifty 50 and BSE-100 returns, as all p-values are well below the 0.01 threshold. These findings validate **Hypotheses H3 and H4**, confirming that India VIX Granger-causes returns on the Nifty 50 and BSE-100 indices (H3), and that these equity returns also Granger-cause movements in India VIX (H4). The bidirectional causality highlights a feedback loop between perceived risk and market performance, consistent with prior studies (e.g., Bhowmik & Wang, 2020; Tripathy, 2017).

ARCH-LM Test for Volatility Clustering

To verify the existence of conditional heteroskedasticity, the ARCH-LM test was applied to Nifty 50 returns, BSE-100 returns, and differenced India VIX (ΔVIX) using five lags. The results (Table 5) decisively reject the null hypothesis of no ARCH effects at the 1% level for all three series, confirming volatility clustering in the data—a stylized fact consistent with financial time series literature (Engle, 1982; Bollerslev, 1986). These findings provide a strong statistical rationale for estimating EGARCH models to capture asymmetric volatility dynamics.

Table 5: ARCH-LM Test Results (Lag = 5)

Series	χ^2 Statistic	df	p-value	Conclusion
Nifty Returns	454.13	5	< 2.2e-16	ARCH effects detected
BSE Returns	408.64	5	< 2.2e-16	ARCH effects detected
Differenced VIX	458.70	5	< 2.2e-16	ARCH effects detected

EGARCH Estimation and Asymmetric Volatility Effects

Building upon the significant volatility clustering identified through the ARCH-LM test (Section 5.6), we estimate Exponential GARCH (EGARCH (1,1)) models to examine asymmetric volatility effects, often referred to as leverage effects. The EGARCH framework, introduced by Nelson (1991), allows for modeling both non-linearity and asymmetry in volatility responses to shocks. This specification is applied to the return series of Nifty 50, BSE-100, and differenced India VIX, thereby capturing the dynamics of conditional variance in response to positive and negative return shocks.

The estimated EGARCH (1,1) parameters (Table 6) show that the gamma coefficient (γ), which captures asymmetry, is positive and highly significant for all series, indicating that negative return shocks induce higher future volatility than positive shocks of similar magnitude. This supports Hypothesis H5, consistent with the findings of Glosten et al. (1993) and Black (1976).

Furthermore, the magnitude of the γ coefficient confirms that the volatility response to negative shocks is not only asymmetric but also significantly larger, empirically validating **Hypothesis H6**. This disproportionate sensitivity aligns with the theoretical expectation of leverage effects in emerging markets and substantiates the relevance of EGARCH modeling in capturing such dynamics.

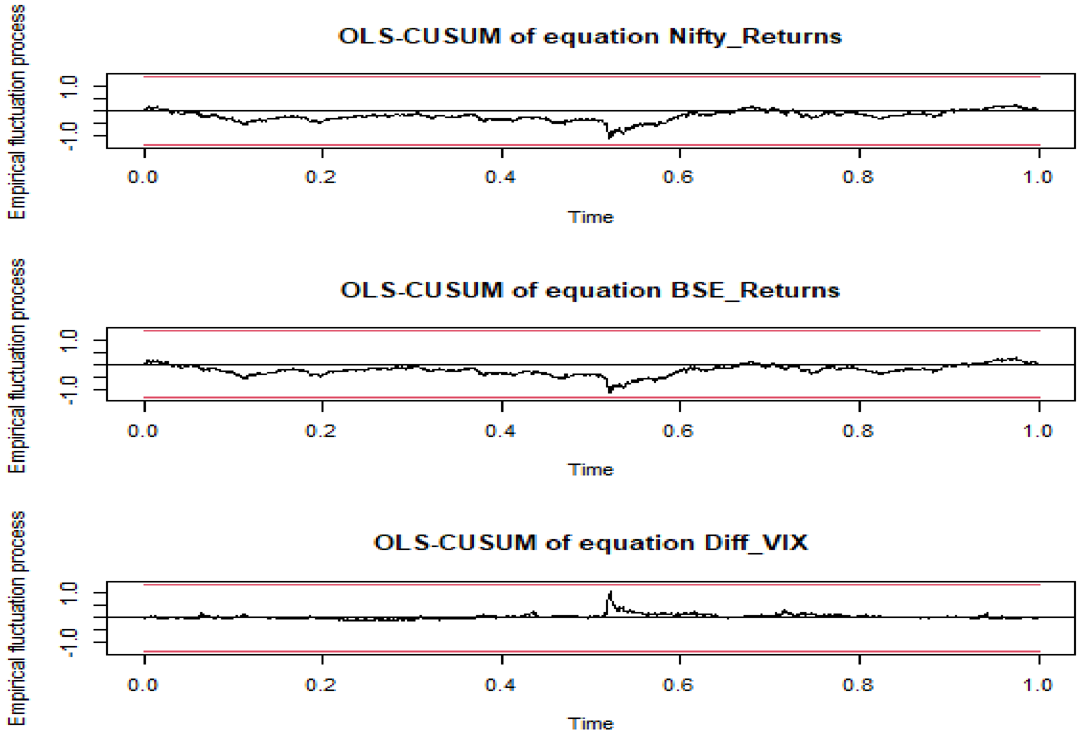
Table 6: EGARCH (1,1) Estimation Results

Variable	Nifty 50 γ	BSE-100 γ	VIX γ	Significance
Asymmetry γ	0.1205	0.1296	0.0720	*** ($p < 0.001$)
α (Shock)	–0.1100	–0.1277	0.1562	***
β (Persistence)	0.9699	0.9610	0.9880	***
Log Likelihood	–3103.12	–3098.13	–2794.53	—

*Significance codes: ***p < 0.001*

All models passed residual diagnostics (Ljung–Box, ARCH-LM, and sign bias tests), validating model adequacy and stability.To ensure the robustness of the VAR model estimations, stability diagnostics were performed using OLS-based cumulative sum (CUSUM) tests. As shown in Figure 2, the CUSUM plots for all three equations—Nifty Returns, BSE Returns, and Diff VIX—remain within the 95% confidence bands, indicating parameter stability over the sample period.

Figure 2: OLS-CUSUM plots for Nifty Returns, BSEReturns, and DiffVIX equations. All stay within confidence bands, indicating model stability.



VAR Model Estimation: Dynamic Interdependence

To evaluate multivariate dynamics between market returns and volatility, a Vector Autoregression (VAR) model was estimated using five lags based on AIC selection. The model captures bidirectional interdependencies among Nifty 50, BSE-100, and differenced VIX.

Significant lagged coefficients of VIX shocks on both Nifty and BSE returns (at lag 2 and 4) confirm that volatility innovations have predictive power over market performance, supporting Hypothesis H3. The model also indicates feedback from returns to implied volatility (Hypothesis H4), although weaker.

Table 7: Selected VAR Coefficient Estimates

Equation	Variable (Lag)	Coefficient	p-value	Significance
Nifty Return	Diff_VIX.l2	–0.1142	<0.001	***
BSE Return	Diff_VIX.l2	–0.1050	<0.001	***
Diff_VIX	Nifty_Returns.l4	–0.6070	0.003	**
Diff_VIX	BSE_Returns.l4	0.5980	0.004	**

*Significance codes: ***p < 0.001, **p < 0.01*

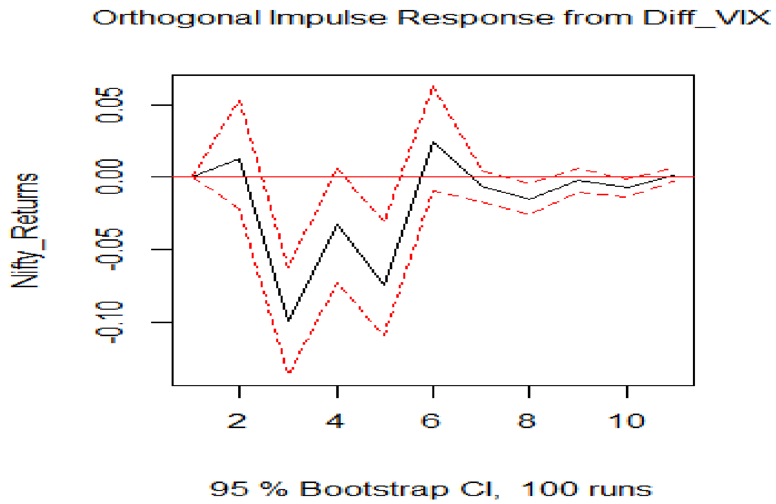
The residual diagnostics confirmed model stability and absence of autocorrelation. The Impulse Response Functions (IRFs) further illustrate that shocks in implied volatility led to a short-term dip in equity returns, peaking around the 2nd and 3rd days post-shock.To understand the dynamic effects of volatility shocks on market returns, Impulse Response

Functions (IRFs) were generated using the VAR (5) model. Specifically, the response of NiftyReturns to a one-unit orthogonal shock in Diff VIX was examined.

As depicted in Figure 3, a sudden increase in implied volatility (India VIX) results in a negative and statistically significant impact on Nifty returns in the short term, with the effect dissipating over time. This finding aligns with risk-aversion theory, where elevated market uncertainty leads to declining returns (Whaley, 2000; Bouri et al., 2021).This dynamic reaction pattern validates **Hypothesis H7**, confirming that innovations in the India VIX produce statistically significant impulse responses in both Nifty 50 and BSE-100 returns. The impulse responses show short-term dips in equity performance, supporting the time-distributed and persistent effects of volatility shocks in emerging market contexts.

Figure 3: Orthogonal impulse response of NiftyReturns to shocks in DiffVIX (95% Bootstrap CI, 100 runs).

Together, the results from causality, variance modeling, and impulse responses reveal



consistent and robust linkages between implied volatility and equity index performance. These insights form the basis of the concluding observations.

CONCLUSION

This study offers a comprehensive exploration of the dynamic interdependencies between implied volatility, as measured by the India VIX, and the daily returns of the Nifty 50 and BSE-100 indices over a decade-long period. The results affirm the existence of statistically significant bidirectional causality between implied volatility and equity returns, reinforcing the feedback loop hypothesis prevalent in financial literature. Granger causality tests confirm that not only does India VIX predict short-term index movements, but index returns themselves also influence volatility expectations, highlighting the reflexive nature of market sentiment and performance.

The presence of volatility clustering, as detected through ARCH-LM tests, underscores the necessity of employing GARCH-type models. The EGARCH (1,1) framework, in particular, successfully captures asymmetrical volatility behaviour—evidenced by significant positive asymmetry coefficients. These results validate the leverage effect; whereby negative market shocks exert a stronger influence on future volatility compared to positive shocks of equal magnitude. This finding is aligned with behavioural finance theories that suggest investor panic disproportionately escalates in declining markets.

Moreover, the VAR model reveals robust multivariate linkages, with VIX innovations exerting lagged negative effects on both Nifty and BSE returns. The inclusion of CUSUM plots further substantiates the temporal stability of the estimated relationships. Impulse response functions visualize these dynamics, showing that volatility shocks induce immediate and statistically significant downward pressure on stock returns, although these effects diminish over time.

Collectively, these insights contribute to a more nuanced understanding of risk–return behaviour in emerging markets. The evidence supports the strategic use of volatility indicators like India VIX in portfolio risk management, asset pricing, and regulatory oversight. As financial markets evolve amid heightened global uncertainty, future research could explore non-linear causal structures, incorporate regime-switching models, or extend the analysis to cross-border volatility transmission patterns to further refine predictive accuracy and policy relevance.

LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

While this study provides important insights into the dynamic interplay between implied volatility and equity returns in India, certain limitations must be acknowledged. First, the analysis is limited to three variables—Nifty 50, BSE-100, and India VIX—without incorporating global volatility indices (e.g., VIX Global or crude oil volatility). Second, structural breaks and regime shifts beyond the pandemic period were not formally modelled. Third, the study employs linear VAR and EGARCH frameworks, which may not fully capture complex non-linearities or tail risks.

Future research could extend this work by applying machine learning models or non-linear causality methods to uncover hidden dynamics. Additionally, examining cross-border volatility spillovers and incorporating macroeconomic or geopolitical risk indices could offer a more comprehensive risk assessment in emerging markets.

REFERENCES

Agarwal, R., & Mishra, A. K. (2010). Stock market volatility: An international comparison. *International Journal of Business and Management*, *5*(5), 49–59. https://doi.org/10.5539/ijbm.v5n5p49

Black, F. (1976). Studies of stock market volatility changes. In Proceedings of the 1976 Meetings of the American Statistical Association, Business and Economic Statistics Section (pp. 177–181).

Bhowmik, R., & Wang, S. (2020). Stock market volatility and international linkages: A study of emerging and developed Asian countries. *International Journal of Finance & Economics*, *26*(4), 6075–6096. https://doi.org/10.1002/ijfe.2087

Bhowmik, R., & Wang, S. (2020). Global financial crisis and stock market integration in South Asia. *Research in International Business and Finance*, *53*, 101209. https://doi.org/10.1016/j.ribaf.2020.101209

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, *31*(3), 307–327. https://doi.org/10.1016/0304-4076(86)90063-1

Bouri, E., Jain, A., &Roubaud, D. (2021). Cryptocurrencies as hedges and safe-havens for US stock sectors. *The North American Journal of Economics and Finance*, *56*, 101346. https://doi.org/10.1016/j.najef.2021.101346

Brooks, C. (2014). *Introductory econometrics for finance* (3rd ed.). Cambridge University Press.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, *74*(366a), 427–431. https://doi.org/10.1080/01621459.1979.10482531

Engle, R. F. (1982). Autoregressive conditional heteroskedasticity with estimates of the variance of UK inflation. *Econometric*, *50*(4), 987–1007. https://doi.org/10.2307/1912773

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The Journal of Finance*, *48*(5), 1779–1801. https://doi.org/10.1111/j.1540-6261.1993.tb05128.x

Granger, C. W. J. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometric*, *37*(3), 424–438. https://doi.org/10.2307/1912791

Kumar, D. (2014). Return and volatility transmission between gold and stock sectors: Application of portfolio management and hedging effectiveness. *IIMB Management Review*, *26*(1), 5–16. https://doi.org/10.1016/j.iimb.2013.12.002

Lutkepohl, H. (2005). New introduction to multiple time series analysis. Springer.

Mishra, R. K., Singh, R. P., & Jain, P. K. (2020). Impact of COVID-19 on performance and volatility of Indian stock market. *International Journal of Economics and Financial Issues*, *10*(5), 236–242. https://doi.org/10.32479/ijefi.10434

Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometric*, *59*(2), 347–370. https://doi.org/10.2307/2938260

Sarwar, G. (2012). Is VIX an investor fear gauge in BRIC equity markets? *Journal of Multinational Financial Management*, *22*(3), 55–65. https://doi.org/10.1016/j.mulfin.2012.02.001

Sharma, A. K., & Singh, B. (2023). Investigating the role of India VIX in the Indian stock market: Evidence from VAR and GARCH models. *Journal of Risk and Financial Management*, *16*(6), 277. https://doi.org/10.3390/jrfm16060277

Sims, C. A. (1980). Macroeconomics and reality. *Econometric*, *48*(1), 1–48. https://doi.org/10.2307/1912017

Tripathy, N. (2017). Forecasting volatility of Indian stock market using GARCH models. *Asian Journal of Research in Banking and Finance*, *7*(7), 22–36.

Tsay, R. S. (2010). *Analysis of financial time series* (3rd ed.). Wiley.

Whaley, R. E. (2000). The investor fear gauge. *The Journal of Portfolio Management*, *26*(3), 12–17. https://doi.org/10.3905/jpm.2000.319728

Ahmed, M. (2020). Volatility modeling in emerging stock markets: Evidence from GARCH models. *Finance Research Letters*, *34*, 101215. https://doi.org/10.1016/j.frl.2019.07.003

Al-Najjar, B. (2014). Corporate governance, tourism growth, and firm performance: Evidence from publicly listed tourism firms in five Middle Eastern countries. *Tourism Management*, *42*, 342–351. https://doi.org/10.1016/j.tourman.2013.09.007

Anand, A., & Mehta, M. (2021). Volatility spillovers and linkages between Indian and global financial markets. *Global Finance Journal*, *50*, 100516. https://doi.org/10.1016/j.gfj.2021.100516

Aslam, F., & Kamal, M. (2021). Market sentiment and volatility: The role of media in the COVID-19 era. *Journal of Behavioral and Experimental Finance*, *29*, 100454. https://doi.org/10.1016/j.jbef.2020.100454

Bouri, E., Jain, A., &Roubaud, D. (2018). Policy uncertainty and Bitcoin returns. *Journal of International Financial Markets, Institutions and Money*, *59*, 118–131. https://doi.org/10.1016/j.intfin.2018.01.003

Engle, R., & Patton, A. J. (2001). What good is a volatility model? *Quantitative Finance*, *1*(2), 237–245. https://doi.org/10.1088/1469-7688/1/2/305

Fernandes, M. (2020). Economic uncertainty, volatility, and stock returns: Evidence from emerging markets. *Emerging Markets Review*, *45*, 100732. https://doi.org/10.1016/j.ememar.2020.100732

Ghosh, A., & Sahoo, S. (2019). Volatility forecasting using GARCH models: Evidence from Indian stock market. *IIM Kozhikode Society & Management Review*, *8*(2), 142–152. https://doi.org/10.1177/2277975219831022

Gupta, R., & Modise, M. P. (2013). South African and BRICS stock markets: A volatility spillover analysis. *Applied Econometrics and International Development*, *13*(1), 167–182.

Hamao, Y., Masulis, R. W., & Ng, V. (1990). Correlations in price changes and volatility across international stock markets. *Review of Financial Studies*, *3*(2), 281–307. https://doi.org/10.1093/rfs/3.2.281

Jain, A., & Bouri, E. (2021). The role of volatility indices in forecasting stock returns: Evidence from India. *Finance Research Letters*, *40*, 101730. https://doi.org/10.1016/j.frl.2020.101730

Kumar, R., & Padhi, P. (2013). Dynamic linkages between Indian VIX and stock market indices. *International Journal of Economics and Financial Issues*, *3*(1), 12–22.

Mishra, A. K., & Apte, P. G. (2017). Volatility modeling in Indian stock market: A sectoral analysis. *Global Business Review*, *18*(5), 1151–1165. https://doi.org/10.1177/0972150917713871

Pattnaik, D., & Dhal, S. C. (2019). Relationship between India VIX and stock market return and volatility. *The IUP Journal of Applied Finance*, *25*(2), 32–42.

Sarwar, G. (2012). Is VIX an investor fear gauge in BRIC equity markets? *Journal of Multinational Financial Management*, *22*(3), 55–65. https://doi.org/10.1016/j.mulfin.2012.02.001

Singh, S., & Pandey, S. (2019). Volatility spillover and dynamic linkages between global and Indian stock markets. *Journal of Advances in Management Research*, *16*(1), 2–17. https://doi.org/10.1108/JAMR-09-2017-0084

Sinha, P. (2016). A study of volatility spillover in Indian stock market using multivariate GARCH models. *Global Business Review*, *17*(1), 147–160. https://doi.org/10.1177/0972150915610726

Tripathy, N. (2011). Causal relationship between macroeconomic indicators and stock market in India. *Asian Journal of Finance & Accounting*, *3*(1), 1–19. https://doi.org/10.5296/ajfa.v3i1.854

Wang, Y. (2019). Investor sentiment and stock market volatility: Evidence from China. *Emerging Markets Finance and Trade*, *55*(5), 1175–1188. https://doi.org/10.1080/1540496X.2018.1454053