Examining the Relationship Between Implied Volatility, Index Returns, and Trading Volume in the Indian Stock Market

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Abstract

Purpose : Investors' short-term fears or expectations are expressed in India through the India Volatility Index, a volatility index based on Nifty call options. The microstructure of the market was largely composed of trading volume, stock index returns, and implied volatility. Understanding the microstructure of the market is crucial because it gives investors important knowledge about its dynamics and empowers them to make wise decisions.

Methodology : For the years 2018 through 2023, the study took into account the closing values of the Nifty, volatility index, and trading volume. To examine the dynamic link between the variables, quantile regression and Granger causality models were applied.

Findings : The findings suggested that the volatility index's lag returns cause fluctuations in the current returns of the Nifty. The Nifty returns and changes in trading volume are unrelated. It is observed that Nifty returns have an asymmetric relationship with returns from the volatility index and a positive association with trading volume. Markets responded more strongly to negative news shocks when the Nifty had negative returns.

Practical Implications : The volatility index would be used by investors as a hedging tool to forecast near-term Nifty volatility as well as diversify the risk in their portfolio.

Originality : The current work investigated a new temporal regime in light of the pandemic era and is an attempt to understand the dynamics of the market since downturns cause markets to become more volatile.

Keywords : implied volatility, index returns, trading volume, contemporaneous, quantile regression

JEL Classification Codes : G13, G14, G15

Paper Submission Date : December 15, 2023 ; Paper sent back for Revision : January 10, 2024 ; Paper Acceptance Date : January 30, 2024 ; Paper Published Online : March 15, 2024

The main areas of interest for market microstructure research include transaction costs, trading volume, and trading behavior. Over the past 20 years, there has been an increase in trading volume across financial assets as a result of technological advancements and changes in trading behavior. Market microstructure is regarded as one of the most important fields of financial research. The Indian stock market now ranks fourth with a

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DOI : https://doi.org/10.17010/ijf/2024/v18i3/173616

market value of USD 4 trillion and 8.49 crore investors. To ascertain the performance of different stocks that can be held in a portfolio, previous researchers used a top-down or bottom-up methodology. These methods, however, did not reveal how markets would respond to the release of "new" information. The 2020 global stock market catastrophe was attributed in part to the novel coronavirus pandemic. As a result, numerous markets had sharp drops in stock returns (Al-Awadhi et al., 2020); in a similar vein, market volatility significantly increased (Baig et al., 2021).

Today, market microstructure analysts are tasked with examining the connections between index returns, trading volume, information flow, and market volatility. Understanding the relationship between these elements shall enable portfolio managers and investors to make use of the information while building an optimal portfolio in which they intend to invest their funds. The implied volatility index (VIX) often provides insights into investors' expectations about market movements in the near term. It is also considered as a measure of future market volatility. The dynamic relationship between implied volatility and other microelements shall help investors predict the level of risk and return from market investments. A strong negative correlation between implied volatility and index returns indicates that markets exhibit higher volatility during market downturns, resulting in low returns from the market. Traders frequently employ implied volatility to put their hedging plans into action. During downturns, investors can utilize options and other derivatives to hedge against possible losses if there is a high correlation between implied volatility and index performance. To take advantage of market timing, traders must comprehend the relationship between implied volatility and trading volume as well as index returns. Suppose high trading volume accompanies an increase in implied volatility and a decline in index returns; it indicates a potential market downturn in the near term, prompting traders to adjust their strategies accordingly. These variables can also provide insights into investors' behavior. High implied volatility and high trading volume during market sell-offs reflect fear-driven trading.

Understanding these behavioral aspects can help investors anticipate market movements and make more informed decisions. Implied volatility, index returns, and trading volume can showcase how a market reacts to the arrival of new information. Once new information or news events alter market sentiment, trade volume surges. A jump in implied volatility shows this. Traders and investors need to handle risk effectively. By understanding how these variables interact, market players can create risk management plans that are specific to various market circumstances. Implied volatility is often considered a reflection of investors' sentiments. A detailed understanding of how changes in sentiment translate into market movements can help investors gauge the broader market mood and make more informed investment choices. By assisting researchers in explaining market behavior and creating more precise and useful financial models, an understanding of the link between these variables also benefits academic research in finance and economics. When a benchmark index's VIX level is high, investors expect substantial fluctuations, and when it is low, they anticipate smaller fluctuations. This phenomenon has emerged as a distinctive asset class that can potentially assist investors in diversifying their portfolio risk, as it exhibits a negative correlation with stock index returns.

Fund managers, traders, and investors will be able to create suitable hedging strategies and diversify their risk by having a clear understanding of the coherence among the microstructure aspects. In this field of study, only a few noteworthy studies have been discovered. The current study, in contrast to other research, attempts to comprehend how various components of the market microstructure interact throughout the pandemic era. The study takes into account a five-year timeframe that spans from 2018 to 2023 and includes pre- and post-pandemic phases.

Literature Review

Muthukamu et al. (2024) revealed that healthcare stocks outperformed pharma stocks; both sectors witnessed abnormal earnings during the pandemic. This enables investors to invest in selective stocks during market downturns confidently. Sahoo and Kumar (2023) found that sectoral indices demonstrated an asymmetric perseverance of volatility in both the short and long run. The magnitude of volatility caused by bad news was higher than that of positive news across all the selected sectors, reducing the scope for risk management by diversification. Nagina (2022) noted that the integration among BRICS stock markets during the pre-and post-pandemic eras was not identical. These differences enable investors to craft hedging strategies to diversify risk and earn high returns. Vo et al. (2022) found that the impact of the pandemic on stock market volatility during the period January 2020 to January 2022 revealed that the pandemic and pandemic control measures initially developed a sense of fear among investors, leading to stock market volatility during 2020.

Investors later developed a notion of herd immunity to volatility, suggesting that stock market volatility fluctuates over time. In 2021, market reactions to the pandemic decreased. Bora and Basistha (2021) found that the Indian stock market experienced high volatility during the pandemic, responding more to bad news shocks. Joshi (2021) found that trading volume and open interest affected volatility in future contracts, but the magnitude of volatility depended on other variables. Dungore and Patel (2021) found that trading volume significantly affected volatility more than interest, but the impact of changes in volume on volatility was low. Syed et al. (2021) examined the consequences of COVID-19 on the Indian stock market and commodity market. Gold and oil represented the commodities market. The results indicated that COVID-19 exhibited a strong negative effect on the stock market and oil prices and a positive effect on gold prices during the first wave. During the second wave, the increase in COVID-19 cases had a positive effect on both stock and commodities markets. This also indicated that a sense of confidence among investors had evolved.

Kamaludin et al. (2021) explored the association between the ASEAN equity markets and daily COVID cases. The study found a strong association among the DJIA and ASEAN markets as the pandemic progressed. Few markets demonstrated strong coherence right from the beginning of the pandemic. Towards the end of the pandemic, all the ASEAN markets exhibited no coherence with either the pandemic or DJIA. Pinto (2022) focused on the Brazilian stock market to investigate the impact of implied volatility on stock returns. The study provided evidence of a negative relationship between implied volatility and stock returns, suggesting that higher implied volatility was associated with lower future stock returns. Siddiqui and Roy (2019) examined the relationship between implied volatility, index returns, and trading volume in India using a quantile regression model (QRM). The study implied an asymmetric relationship of stock returns with changes in volatility and volume, indicating the existence of a contemporary negative relationship between return–volatility and volatility volume. The positive lagged effect of changes in volatility on trading volume supported the sequential arrival of information. Alhussayen (2022) investigated the Saudi Arabian stock market to explore the relationship between trading volume and stock market returns. The findings indicated that trading volume had a significant impact on stock returns, with higher trading volume leading to increased returns. Kumar et al. (2012) found evidence of a positive relationship between trading volume and market volatility during market downturns, and trading volume was associated with market turmoil.

Mishra (2014) investigated the dynamics of volatility in the Indian stock market and observed an upward trend in volatility levels, which exhibited investor sentiments. When India VIX registers high levels, investors tend to anticipate increased fluctuations in the benchmark index, Nifty, which implies that India VIX can act as a hedging tool during adverse market conditions. These findings also coincided with the studies by Kumar (2012) and Chandra and Thenmozhi (2015). Naik et al. (2018) examined the relationship between stock market volatility and trading volume in the Johannesburg Stock Exchange. They found that stock returns responded more to bad news shocks than to good news shocks, and volume and volatility exhibited a positive relationship. Jiang and Tian (2005) captured the patterns in VIX returns during extreme market conditions. They found that VIX returns exhibited a strong and positive relationship with extreme market conditions, specifically steep declines. Gul and

Javed (2009) measured the relationship between trading volume and returns in the Karachi Stock Exchange, and their results indicated a positive relationship between the variables. Tripathy (2010) analyzed the relationship between trading volume and stock returns in the Indian stock market and found that an asymmetric contemporary relationship between the variables and also information may flow simultaneously rather than being sequential. Mehrabanpoor et al. (2011) investigated the association between the stock indices and trading volume in Tehran and found a positive relationship among the variables. Kumar and Singh (2009) examined the relationship between the stock index and sector indices and found that there was no evidence of either co-integration or causation among the selected variables.

Several studies have been undertaken to model the relationship between index returns and implied volatility across various markets. Studies show that implied volatility and index returns have a strong asymmetric relationship. Similarly, studies examining the association between index returns and trading volume indicate a positive relationship among the variables. Past literature also indicates that the impact of the pandemic slowly decayed, resulting in reduced stock market volatility during the second wave in most markets. Very few studies have explored all the market microstructure elements. Given that the global stock indices saw a sharp decline due in part to the coronavirus outbreak, it is imperative to investigate the components of the market microstructure during these times.

Research Methodology

It is a descriptive research design that has been used. The major variables in this study are implied volatility, stock index, and trading volume, with the goal of analyzing the market microstructure of the Indian stock market. Empirical measures of implied volatility, stock index, and trading volume are the India VIX, Nifty 50, and the number of shares traded in that order. The National Stock Exchange's official website (www.nseindia.com) provides the daily closing prices or values for all three variables for the 5 years beginning on January 1, 2018, and ending on August 31, 2023. The daily log returns were calculated using the following formula in order to meet the study's objectives:

$$R = \text{Ln}\,(P_t / P_{(t-1)}) \qquad \ldots\ldots\ldots\ldots\ldots (1)$$

where,
Ln = Natural logarithm,
P_t = Closing price on day t,
P_{t-1} = Closing price on day t–1.

Analytical tools such as descriptive statistics, the Augmented Dickey-Fuller (ADF) test, the Granger causality test, ordinary least squares (OLS), and the QRM were used to test the relationships. The analysis was conducted using EViews software. In the study, Implied Volatility is denoted as VIX, stock index as Nifty, and trading volume as volume. Positive and negative returns in the stock index are denoted as PR and NR, respectively.

Objectives of the Study

(1) To examine if any casual relation exists among the variables.

(2) To explore the impact of index returns on implied volatility and during extreme market conditions.

(3) To examine the relation between index returns, trading volume, and implied volatility.

Analysis and Results

This study attempts to understand the nature of the relationship and the impact of index returns on implied volatility and trading volume. Financial time series data for the period from 2018 to 2023 were obtained from secondary sources.

- **H_{01} :** The data is normally distributed.
- **H_{a1} :** The data is not normally distributed.

The comprehensive data displayed in Table 1 suggests that the Nifty 50, India VIX, and volume mean values are in proximity to zero. Volume has been more volatile than VIX, according to the standard deviation. In general, skewness is 0, and kurtosis is 3 when a series is normally distributed. However, the distribution of the variables is not symmetric, as indicated by the non-zero skewness. Specifically, the skewness of Nifty is negative, implying long left tails, suggesting that investors had a high probability of earning negative returns.

In contrast, the skewness of VIX and volume is positive, implying long right tails. Similarly, the coefficients of kurtosis are found to be positive for all variables and greater than 3. The results of the Jarque–Bera test show that the distribution is not normally distributed, as the p-value is < 0.05. Hence, the null hypothesis H_{01}, which states that the data is normally distributed, is rejected.

- **H_{02} :** The data is non-stationary.
- **H_{a2} :** The data is stationary.

Table 1. *Descriptive Statistics*

Parameter	*Nifty*	*VIX*	*Volume*
Mean	0.000	0.000	0.002
Median	0.001	–0.003	–0.001
Maximum	0.084	0.268	2.251
Minimum	–0.139	–0.353	–2.264
Std. Dev.	0.012	0.052	0.284
Skewness	–1.538	0.705	0.224
Kurtosis	24.446	8.020	17.442
Sum Sq. Dev.	0.193	3.720	111.417
Jarque–Bera	27,127	1,572	12,065
Probability	0.000*	0.000*	0.000*
Observations	1,387	1,387	1,387

Note. *significant at the 5% level.

Table 2. *ADF Test*

Variable	1% level	5% level	10% level	*t*-Statistic	Prob.*
Nifty	–3.435	–2.863	–2.568	–12.842	0.000*
VIX	–3.435	–2.863	–2.568	–37.699	0.000*
Volume	–3.435	–2.863	–2.568	–23.207	0.000*

Note. *significant at 5% level.

With p-values less than 0.05, the ADF test results shown in Table 2 show that the variables are stable. H_{02} is thus rejected as the null hypothesis.

The lag length to establish the VAR framework was chosen using the lag selection criterion. The Granger causality test results presented in Table 3 indicate that the χ^2 and the p-values of null hypothesis H_{04} (Nifty does not Granger cause VIX), H_{06} (Nifty does not Granger cause volume), H_{08} (Nifty does not Granger cause volume), H_{07} (Volume does not Granger cause VIX), and H_{05} (Volume does not Granger Cause Nifty) are insignificant and hence cannot be rejected. The null hypothesis H_{03} (VIX does not Granger cause Nifty) can be rejected as the p-value is

Table 3. ***VAR Granger Causality/Block Exogeneity Wald Tests***

Variable	χ^2	***df***	**Prob.**
H_{03}: VIX does not Granger cause Nifty.			
H_{a3}: VIX Granger causes Nifty.			
Dependent Variable : *NIFTY*			
VIX	34.749	7	0.000*
All	34.749	7	0.000*
H_{04} : Nifty does not Granger cause VIX.			
H_{a4} : Nifty Granger causes VIX.			
Dependent Variable : *VIX*			
NIFTY	8.315	7	0.306
All	8.315	7	0.306
H_{05}: Volume does not Granger cause Nifty.			
H_{a5} : Volume Granger causes Nifty.			
Dependent Variable : *NIFTY*			
VOLUME	5.374	7	0.614
All	5.374	7	0.614
H_{06} : Nifty does not Granger cause Volume.			
H_{a6} : Nifty Granger causes Volume.			
Dependent Variable : *VOLUME*			
NIFTY	6.1324	7	0.524
All	6.1324	7	0.524
H_{07} : Volume does not Granger cause VIX.			
H_{a7} : Volume Granger causes VIX.			
Dependent Variable : *VIX*			
VOLUME	6.229	8	0.622
All	6.229	8	0.622
H_{08} : VIX does not Granger cause Volume.			
H_{a8} : VIX Granger causes Volume.			
Dependent variable : *VOLUME*			
VIX	13.163	8	0.106
All	13.163	8	0.106

Note. *significant at the 5% level.

Table 4. ***Regression Analysis – VIX as the Dependent Variable***

Variable	Coefficient	Std. Error	*t*-Statistic	Prob.
Nifty Positive Returns *(PR)*	–1.409	0.143	–9.858	0.000*
Nifty Negative Returns *(NR)*	–1.908	0.186	–10.231	0.000*
VOLUME	0.008	0.004	1.840	0.066
C	0.000	0.001	0.320	0.749
R-squared	0.203	Akaike info criterion		–3.304
Adjusted *R*-squared	0.201	Schwarz criterion		–3.289
F-statistic	117.320	Hannan–Quinn criterion		–3.299
Prob (*F*-statistic)	0.000*	Durbin–Watson stat.		2.013

Note. *significant at the 5% level.

Table 5. ***Residual Test***

Test	*F*-statistic	Obs**R*-squared	Prob.
Breusch–Godfrey Serial Correlation LM Test	0.395	0.794	0.673
ARCH Heteroskedasticity Test	30.889	30.259	0.000*

Note. *significant at the 5% level.

significant. The results indicate that uni-directional causation runs from VIX to Nifty. The lagged returns of VIX cause changes in the present returns of Nifty. The results contradict the findings by Siddiqui and Roy (2019).

The QRM is widely employed to explore the relationship between variables, as it offers advantages over the OLS model and is grounded on median values. The regression estimates are derived using the OLS technique. If the residuals of the OLS model display heteroskedasticity or autocorrelation, the QRM is then estimated.

As can be seen from the OLS estimates in Table 4, the returns of VIX are asymmetrically affected by both positive and negative Nifty returns. It is suggested that the model is stable by the Durbin–Watson statistic and the significant probability value. Testing the residuals will lead to the model fit being confirmed. A normal distribution, absence of serial or autocorrelation, and heteroskedasticity are essential characteristics of the residuals of an OLS estimate.

The serial correlation LM test and ARCH test were conducted to examine the residuals. The test results in Table 5 indicate that the residuals exhibit heteroskedasticity. Therefore, the QRM is adopted.

The QRM estimates in Table 6 indicate that both positive and negative returns of Nifty have an asymmetric effect on VIX returns. Changes in volume do not have a significant impact on VIX returns. Negative returns of

Table 6. ***Quantile Regression – VIX as the Dependent Variable***

Variable	Coefficient	Std. Error	*t*-Statistic	Prob.
PR	–1.730	0.209	–8.286	0.000*
NR	–2.585	0.430	–6.011	0.000*
VOLUME	0.000	0.005	0.087	0.931
C	–0.003	0.002	–1.832	0.067
Pseudo *R*-squared	0.114	Quasi-LR statistic		255.006
Adjusted *R*-squared	0.112	Prob(Quasi-LR stat.)		0.000*

Note. *significant at the 5% level.

Table 7. *Quantile Process Coefficients*

Quantile	*PR*		*NR*		Constant	
	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.
0.1	–1.583	0.000*	–2.117	0.000*	–0.047	0.000*
0.2	–1.771	0.000*	–2.292	0.000*	–0.031	0.000*
0.3	–1.705	0.000*	–2.258	0.000*	–0.020	0.000*
0.4	–1.661	0.000*	–2.366	0.000*	–0.012	0.000*
0.5	–1.730	0.000*	–2.585	0.000*	–0.003	0.067
0.6	–1.621	0.000*	–2.621	0.000*	0.006	0.001*
0.7	–1.493	0.000*	–2.602	0.000*	0.016	0.000*
0.8	–1.124	0.007*	–2.598	0.000*	0.027	0.000*
0.9	–1.195	0.000	–2.743	0.000*	0.045	0.000*

Note. *significant at the 5% level.

Table 8. *Regression Analysis – Nifty as the Dependent Variable*

Variable	Coefficient	Std. Error	*t*-Statistic	Prob.
VIX	–0.115	0.005	–21.602	0.000*
VOLUME	0.000	0.001	0.258	0.796
C	0.000	0.000	1.423	0.155
R-squared	0.252	Akaike info criterion		–6.327
Adjusted *R*-squared	0.251	Schwarz criterion		–6.316
F-statistic	233.716	Hannan–Quinn criterion		–6.323
Prob(*F*-statistic)	0.000*	Durbin–Watson stat		2.126

Note. *significant at the 5% level.

Nifty cause greater fluctuations in VIX than positive returns. Nifty returns can explain changes in VIX to an extent of 11%.

The findings shown in Table 7 suggest that there is a trend in the implied volatility index returns and that the constant is significant in all quantiles, with the exception of the fifth quantile. As we go from the lower quantile to the upper quantile, the slope coefficients of NR rise in absolute terms. This indicates a significant and strong relationship between the variables during extreme market conditions. Hence, the null hypothesis "There is no asymmetric relationship between the Stock Index returns (Nifty 50 returns) and the Implied Volatility Index returns (India IX returns) throughout the distribution curve" can be rejected. There exists an asymmetric relationship between the variables across all quantiles, as found by Siddiqui and Roy (2019), Chandra and Thenmozhi (2015), and Kumar (2012).

The OLS estimates in Table 8 indicate that VIX returns have an asymmetric effect on Nifty returns. The Durbin–Watson statistic and the significant probability value indicate that the model is stable. Testing the residuals will result in confirmation of the model fit. An OLS estimate's residuals must be normally distributed, devoid of serial or autocorrelation, and heteroskedasticity.

The serial correlation LM test and ARCH test were conducted to examine the residuals. The test results in Table 9 indicate that the residuals exhibit heteroskedasticity. Therefore, the QRM is adopted.

The QRM estimates in Table 10 indicate that Nifty returns and VIX returns are asymmetric. Changes in volume do not have any significant impact on Nifty returns, as the slope coefficient is 0.

Table 9. ***Residual Test***

Test	*F*-statistic	Obs*R-squared	Prob.
Breusch–Godfrey Serial Correlation LM Test	2.771	5.540	0.063*
ARCH Heteroskedasticity Test	106.650	99.163	0.000*

Note. *significant at the 5% level.

Table 10. ***Quantile Regression – Nifty as the Dependent Variable***

Variable	Coefficient	Std. Error	*t*-Statistic	Prob.
VIX	–0.114	0.007	–15.394	0.000*
VOLUME	–0.001	0.001	–2.044	0.041*
C	0.000	0.000	0.865	0.387
Pseudo *R*-squared	0.157	Quasi-LR statistic		368.469
Adjusted *R*-squared	0.156	Prob(Quasi-LR stat.)		0.000*

Note. *significant at the 5% level.

Table 11. ***Quantile Process Coefficients***

Quantile	*VIX*		*Volume*		Constant	
	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.
0.1	–0.121	0.000*	–0.003	0.097	–0.009	0.000*
0.2	–0.118	0.000*	–0.003	0.004*	–0.005	0.000*
0.3	–0.121	0.000*	–0.002	0.000*	–0.003	0.000*
0.4	–0.120	0.000*	–0.002	0.014*	–0.002	0.000*
0.5	–0.114	0.000*	–0.001	0.041*	0.000	0.387*
0.6	–0.108	0.000*	–0.002	0.022*	0.002	0.000*
0.7	–0.106	0.000*	–0.001	0.332	0.004	0.000*
0.8	–0.094	0.000*	0.001	0.223	0.006	0.000*
0.9	–0.089	0.000*	0.002	0.006*	0.010	0.000*

Note. *significant at the 5% level.

The results presented in Table 11 indicate that the constant is significant in all quantiles except the fifth quantile, implying a trend in Nifty returns. The slope coefficients of VIX increase and decrease in absolute terms as we move from the lower quantile to the upper quantile. This indicates a significant but weak relationship between the variables during extreme market conditions. Therefore, the null hypothesis "There is no asymmetric relationship between the Stock Index returns (Nifty 50 returns) and the Implied Volatility Index returns (India VIX returns) throughout the distribution curve" can be rejected. There exists an asymmetric relationship between the variables across all quantiles.

A positive correlation has been seen between trading volume and positive returns of the Nifty, as indicated by the quantile regression results presented in Table 12. This suggests that there is an increase in the volume of shares traded when the Nifty tends to move higher. In contrast, the trade volume falls in tandem with a reduction in the Nifty. This shows that there is a symmetric movement between Nifty and trade volume.

Table 12. *Quantile Regression – Volume as the Dependent Variable*

Quantile Regression – Volume as the Dependent Variable				
Variable	**Coefficient**	**Std. Error**	***t*-Statistic**	**Prob.**
Nifty Positive Returns *(PR)*	3.08	0.65	4.76	0.00
Nifty Negative Returns *(NR)*	–3.87	1.28	–3.01	0.00
C	–0.02	0.01	–2.50	0.01
Pseudo *R*-squared	0.009	Quasi-LR statistic		18.187
Adjusted *R*-squared	0.007	Prob(Quasi-LR stat.)		0.000

Conclusion

The study aims to understand the relationship between implied volatility, index returns, and trading volume. It indicates uni-directional causation running from implied volatility to index returns, suggesting that lagged returns of VIX affect the present returns of Nifty in the short run. Similarly, there is no causation running from either trading volume to index returns or from implied volatility to trading volume. The quantile regression results indicate that index returns have an asymmetric effect on implied volatility, with negative returns in the index leading to an increase in implied volatility. However, positive returns have a positive impact on trading volume, albeit with a low *R*-squared value. Trading volume does not impact implied volatility or Nifty returns. Consequently, it may be said that index returns show a symmetric connection with trading volume and an asymmetric relationship with implied volatility. In conclusion, investors can forecast future Nifty returns using VIX as a tool and adjust their trading methods accordingly.

Practical Implications

Fund managers, traders, and investors may think about incorporating VIX in their portfolios to protect against risk during volatile market conditions because of the asymmetric relationship that exists between implied volatility and index returns at all times. Similarly, VIX tends to provide meaningful information to portfolio managers when predicting future market volatility. Assessing future market volatility can assist fund managers in making informed decisions while constructing an optimal portfolio.

Limitations of the Study and Scope for Further Research

The study is restricted to a few market microstructure characteristics and the Indian market. Even after taking into account a number of factors, the random walk has consistently remained a crucial component of stock markets worldwide. This study only looks at return spillover; volatility spillovers have not yet been analyzed. The present study considers a sample period of 5 years, spanning from 2018 to 2023. The sample period was chosen to encompass the pandemic era. In the future, researchers may consider breaking down this sample period into smaller time frames, such as pre-pandemic (2018–2019), during the pandemic (2020–mid-2021), and post-pandemic (mid-2021–mid-2023). Breaking down the sample into smaller segments can provide more precise information on the behavior of the study variables. Additionally, the application of models like VECH or BEKK GARCH can offer insights into volatility spillovers.

Authors' Contribution

P. B. Saranya conceived the idea and developed both qualitative and quantitative designs to undertake the empirical study. Dr. R. K. Sudhamathi extracted research papers based on keywords, developed the literature review, and obtained the required data. P. B. Saranya verified the tools and conducted the analysis using EViews. Both the authors co-authored the manuscript.

Conflict of Interest

The authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

Funding Acknowledgment

The authors received no financial support for the research, authorship, and/or for the publication of this article.

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