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India VIX and NIFTY 50 Volatility: Predictive Evidence and GARCH-X Forecasting

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Abstract:
This study examines whether India VIX contains predictive information about NIFTY 50 volatility using daily data from 1 January 2015 to 31 July 2026, obtained from the National Stock Exchange of India (NSE). Future realized volatility is measured over a 22-trading-day horizon. The study employs predictive regressions with Newey–West standard errors, asymmetric return–VIX analysis, a COVID-19 interaction model, and an out-of-sample comparison of GARCH(1,1) and GARCH-X models. The results show that India VIX significantly predicts subsequent NIFTY 50 realized volatility and retains significant predictive power after controlling for preceding realized volatility, with an elasticity of 0.793. Negative NIFTY 50 returns generate a significantly stronger VIX response than positive returns, indicating an asymmetric market-fear response. However, the VIX–volatility relationship is not significantly stronger during the specified COVID-19 period. The GARCH-X model incorporating India VIX-implied variance also improves out-of-sample forecasting, reducing variance MSE by approximately 7.70% relative to GARCH(1,1). Overall, India VIX provides useful incremental and forward-looking information for assessing volatility in the Indian equity market.
***Keywords**: India VIX; NIFTY 50; realized volatility; volatility forecasting; GARCH-X; market fear*

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I. Introduction

Volatility is an important feature of financial markets and has significant implications for investment decisions, portfolio management and risk assessment. Since future volatility is not directly observable, investors and financial institutions rely on historical market movements and forward-looking indicators to assess expected market risk. In India, the India Volatility Index (India VIX), derived from NIFTY option prices, represents the market's expectation of near-term volatility and is commonly viewed as an indicator of market fear and uncertainty.

A key empirical question is whether India VIX merely reflects volatility already observed in the market or contains additional information about future volatility. If India VIX remains significantly associated with subsequent NIFTY 50 volatility after controlling for recently realized volatility, it can be regarded as a useful forward-looking risk indicator. This distinction is important because historical realized volatility reflects past market movements, whereas India VIX incorporates expectations embedded in current option prices.

The relationship between market returns and India VIX may also be asymmetric. Market declines can generate greater uncertainty and demand for downside protection, causing implied volatility to respond more strongly to negative returns than to comparable positive returns. Such asymmetry may reflect heightened investor fear as well as rational reassessment of downside risk, hedging demand and changes in the volatility risk premium. India VIX should therefore not be interpreted as a pure measure of irrational investor sentiment.

The COVID-19 pandemic provides an important stress episode for examining this relationship, as both India VIX and equity-market volatility reached exceptional levels during the crisis. However, higher VIX levels during a crisis do not necessarily imply that its predictive relationship with future realized volatility becomes stronger. This requires explicit empirical testing.

The present study examines the predictive relationship between India VIX and NIFTY 50 realized volatility using daily NSE data from 1 January 2015 to 31 July 2026. It investigates whether India VIX predicts volatility realized over the subsequent 22 trading days, whether this relationship persists after controlling for preceding realized volatility, whether India VIX responds asymmetrically to positive and negative NIFTY 50 returns, and whether its predictive relationship changes during the specified COVID-19 period. The study further evaluates whether incorporating India VIX-implied variance into a GARCH-X model improves out-of-sample volatility forecasts relative to a conventional GARCH(1,1) model.

The study contributes by combining these questions within a single updated empirical framework using directly collected NSE data. By linking option-implied volatility with subsequent realized volatility and out-of-sample forecasting performance, the analysis provides evidence on the usefulness of India VIX as a complementary forward-looking indicator of risk in the Indian equity market.

II. Literature Review

Investor Sentiment, India VIX and Market Volatility

Investor sentiment and market expectations can influence asset prices and volatility beyond changes in fundamental information. Baker and Wurgler (2006, 2007) established the relevance of investor sentiment in explaining stock-market behaviour. In the Indian context, Kumari and Mahakud (2015, 2016) found that investor sentiment contains predictive information for stock-market volatility, while Haritha and Rishad (2020) also reported a significant relationship between sentiment and volatility.

Volatility indices provide a market-based measure of expected uncertainty. Whaley (2000) described the volatility index as an "investor fear gauge." In India, India VIX, derived from NIFTY option prices, reflects expected near-term market volatility. Banerjee (2019) further demonstrated its relevance as a measure of market sentiment. However, India VIX should not be interpreted solely as irrational fear, since it may also incorporate rational volatility expectations, risk aversion, hedging demand and volatility risk premia. This distinction is consistent with the conceptual treatment adopted in the present study.

If India VIX is genuinely forward-looking, higher current values should be associated with higher volatility subsequently realized in the NIFTY 50. More importantly, this relationship should remain significant even after controlling for volatility observed in the recent past.

Asymmetric Market Response and Crisis Period

Stock-market volatility frequently responds asymmetrically to market gains and losses. Declining markets may generate greater uncertainty, stronger demand for downside protection and heightened investor fear. Consequently, negative returns may produce a stronger response in implied volatility than positive returns of comparable magnitude.

The COVID-19 pandemic provides an important setting for examining whether the VIX–volatility relationship changes during periods of extreme uncertainty. Although India VIX increased sharply during the pandemic, a higher VIX level does not necessarily imply that its predictive relationship with subsequent volatility became stronger. This distinction requires formal empirical testing.

Volatility Forecasting and Research Gap

The ARCH framework introduced by Engle (1982) and the GARCH model developed by Bollerslev (1986) provide established approaches for modelling time-varying financial-market volatility. A conventional GARCH model relies mainly on historical returns and conditional variance. If India VIX contains additional forward-looking information, incorporating VIX-implied variance into a GARCH-X model should improve volatility forecasts.

Existing studies establish relationships among investor sentiment, implied volatility and stock-market volatility.

III. Objectives and Hypotheses

Objectives of the study

1. To examine the predictive relationship between India VIX and subsequent NIFTY 50 realized volatility, including its predictive ability after controlling for preceding realized volatility.
2. To analyse the asymmetric response of India VIX to positive and negative NIFTY 50 returns and examine whether its predictive relationship with realized volatility differs during the COVID-19 stress period.
3. To evaluate whether incorporating India VIX-implied variance into a GARCH-X model improves out-of-sample NIFTY 50 volatility forecasting compared with the conventional GARCH(1,1) model.

Hypotheses of the study

H1: Higher India VIX is significantly associated with higher NIFTY 50 volatility realized over the subsequent 22 trading days.

H2: India VIX retains significant predictive power for subsequent NIFTY 50 realized volatility after controlling for preceding 22-day realized volatility.

H3: Negative NIFTY 50 returns generate a significantly stronger India VIX response than positive returns of equivalent magnitude.

H4: The predictive relationship between India VIX and subsequent NIFTY 50 realized volatility is significantly stronger during the specified COVID-19 stress period.
H5: A GARCH-X model incorporating lagged India VIX-implied variance provides more accurate out-of-sample forecasts of NIFTY 50 variance than a conventional GARCH(1,1) model.

IV. Data and Research Methodology

Data and Variables

The study uses daily NIFTY 50 and India VIX data obtained from the National Stock Exchange of India (NSE) for the period 1 January 2015 to 31 July 2026. The two series were matched by common trading dates. NIFTY 50 closing values were used to calculate market returns, while India VIX closing values were used as the measure of option-implied expected volatility.
Daily NIFTY 50 log returns were calculated as:

where P and P represent the NIFTY 50 closing values on the current and preceding trading days, respectively.
The principal dependent variable is annualized volatility realized over the subsequent 22 trading days, approximating one trading month:

To control for recently observed volatility, preceding 22-day realized volatility was similarly calculated using returns from the previous 22 trading days.
For GARCH-X estimation, India VIX was converted into daily implied variance as:

Predictive Regression Models

The baseline model examines whether India VIX predicts subsequently realized NIFTY 50 volatility:

The second model controls for preceding realized volatility:

Since consecutive forward 22-day volatility observations contain overlapping returns, Newey–West HAC standard errors with 22 lags were employed to address heteroskedasticity and serial correlation.

Asymmetry and COVID-19 Analysis

To examine whether India VIX responds differently to market gains and losses, NIFTY 50 returns were separated into positive and negative components:

The asymmetric model was estimated as:

A significantly larger response to negative returns provides evidence of an asymmetric market-fear response.
The COVID-19 effect was examined using a dummy variable equal to 1 from 11 March 2020 to 30 June 2021 and 0 otherwise. An interaction between the COVID dummy and log India VIX was included to test whether the VIX–future volatility relationship became significantly stronger during the specified crisis period.

GARCH Forecasting

A conventional GARCH(1,1) model was estimated as the benchmark:

It was compared with a GARCH-X model incorporating lagged India VIX-implied variance:

The sample was divided chronologically into 80% estimation and 20% out-of-sample evaluation periods. Forecast performance was compared using Mean Squared Error (MSE) and QLIKE loss, with lower values indicating better forecasting performance.

Empirical Results and Findings

The empirical analysis is based on the matched daily NIFTY 50 and India VIX observations for 1 January 2015 to 31 July 2026. After matching common trading dates, 2,868 observations were available.

Construction of the forward and backward 22-day volatility windows resulted in 2,824 observations for the main predictive regressions.

Descriptive Statistics

Table 1. Descriptive Statistics

Variable	Mean	SD	Minimum	Median	Maximum
NIFTY 50 Return (%)	0.036	1.027	-13.904	0.058	8.400
Absolute Return (%)	0.697	0.756	0.000	0.515	13.904
India VIX	16.640	6.085	9.150	15.398	83.608
Forward RV22 (%)	14.170	8.096	5.292	12.320	86.831

NIFTY 50 returns exhibit substantial non-normality, with a Jarque–Bera statistic of 47,116.64 ($p < .001$). India VIX averaged 16.640 but reached a maximum of 83.608, indicating periods of exceptional market uncertainty. The correlation of India VIX with daily NIFTY returns was −0.089, compared with 0.507 with absolute returns, suggesting that VIX is more closely associated with the magnitude of market movements than with return direction.

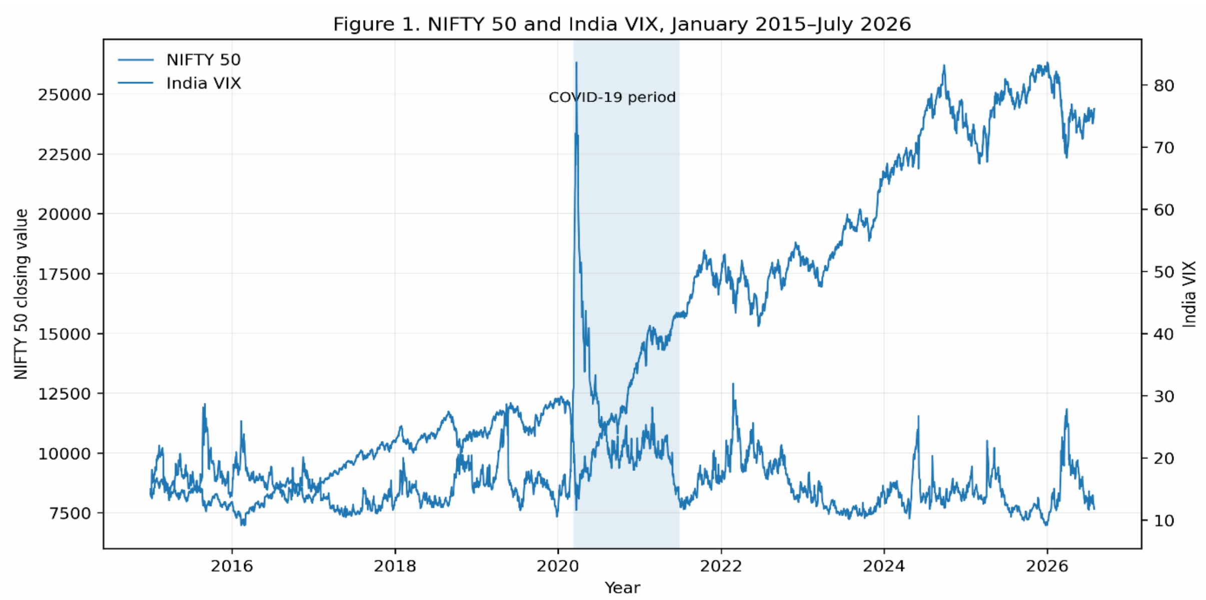

Figure 1. NIFTY 50 and India VIX, January 2015–July 2026
Source: Authors' computation based on NSE data.

Predictive Ability of India VIX

Table 2. Predictive Regression Results

Variable	Model 1: Baseline	Model 2: Past RV Control	Model 3: COVID
Log India VIX	**0.919*****	**0.793*****	**0.865*****
Lagged Log RV22	—	0.109	0.097
COVID Dummy	—	—	-0.371
VIX × COVID	—	—	0.082
R^2	0.420	0.424	0.431

*Note: Newey–West HAC standard errors are used. *** $p < .001$.*

India VIX significantly predicts subsequent 22-day realized volatility. In Model 1, the coefficient of 0.919 ($p < .001$) indicates that a 10% increase in India VIX is associated with approximately a 9.19% increase in subsequent realized volatility.

After controlling for preceding realized volatility, the India VIX coefficient remains highly significant at 0.793 ($p < .001$), while lagged realized volatility is insignificant ($p = 0.243$). India VIX therefore contains incremental information about future volatility. H1 and H2 are supported.

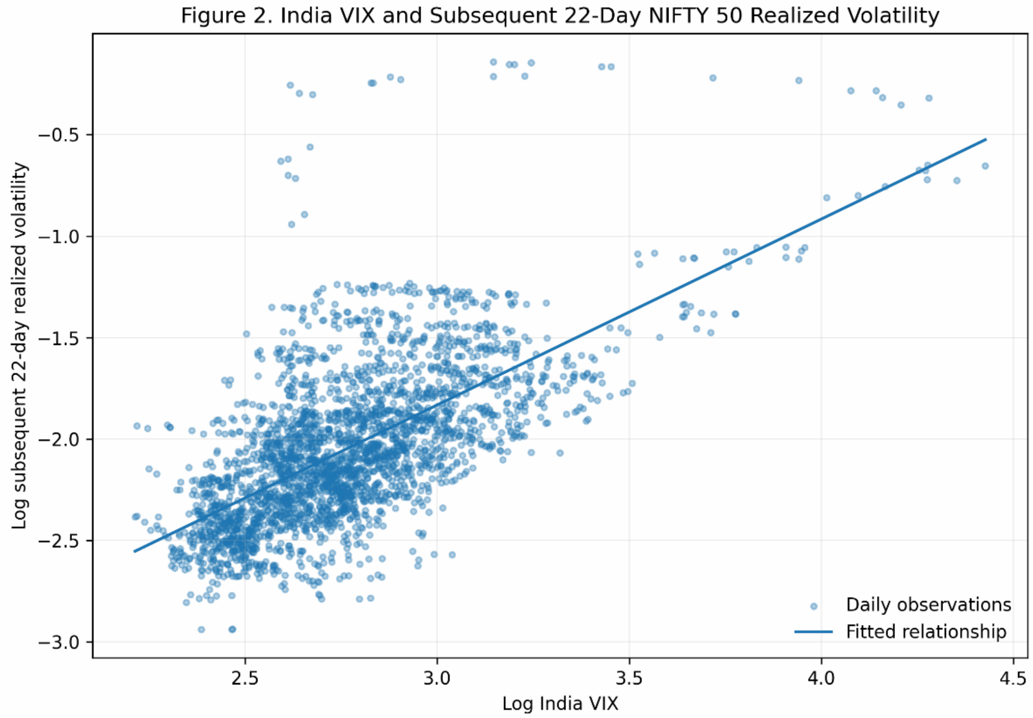

Figure 2. Relationship between India VIX and Subsequent 22-Day NIFTY 50 Realized Volatility
Source: Authors' computation based on NSE data.

The COVID interaction coefficient is positive but statistically insignificant ($\beta = 0.082$, $p = 0.586$). Thus, although market uncertainty was exceptionally high during the pandemic, the predictive relationship between India VIX and subsequent volatility was not significantly stronger during the specified COVID period. H4 is not supported.

Asymmetric Response to Market Returns

Table 3. Asymmetric Return–VIX Regression

Variable	**Coefficient**	**HAC SE**	**t-statistic**	**p-value**
Positive Return	-2.045	0.237	-8.64	< .001
Negative Return	-3.663	0.719	-5.09	< .001

The response of India VIX to negative returns is approximately 1.79 times the magnitude of its response to positive returns. The difference between the coefficients is statistically significant ($p \approx 0.025$), indicating that market declines generate a stronger VIX response than comparable market gains. Therefore, H3 is supported.

GARCH and Out-of-Sample Forecasting

Table 4. GARCH Estimation and Forecast Performance

Measure	**GARCH(1,1)**	**GARCH-X**
α	0.092	0.079
β	0.889	0.492
VIX variance coefficient (γ)	—	0.311
Log likelihood	7,581.89	**7,612.97**
Out-of-sample MSE	4.480 × 10	**4.134 × 10**
QLIKE	-8.593	**-8.690**

The conventional GARCH model exhibits high volatility persistence ($\alpha + \beta = 0.981$). Incorporating India VIX-implied variance improves both model fit and out-of-sample forecasting. GARCH-X reduces variance MSE by approximately 7.70%, while also producing a lower QLIKE loss. Thus, H5 is supported.

Summary of Hypothesis Testing

Table 5. Hypothesis Results

Hypothesis	Result
H1: India VIX predicts subsequent realized volatility	***Supported***
H2: VIX remains predictive after controlling for past volatility	***Supported***
H3: Negative returns generate a stronger VIX response	***Supported***
H4: VIX predictive relationship strengthens during COVID-19	***Not Supported***
H5: GARCH-X improves out-of-sample forecasting	***Supported***

Overall, the results show that India VIX contains incremental forward-looking information about NIFTY 50 volatility, exhibits a significant asymmetric response to market declines, and improves volatility forecasting when incorporated into a GARCH framework.

V. Discussion

The findings demonstrate that India VIX contains meaningful forward-looking information about NIFTY 50 volatility. Its significant relationship with subsequent 22-day realized volatility remains even after controlling for preceding realized volatility. This supports the view that option prices incorporate information about expected market risk beyond that available from recent market movements. The result is broadly consistent with earlier Indian studies reporting a relationship between investor sentiment and market volatility (Kumari & Mahakud, 2015, 2016; Haritha & Rishad, 2020).

The study also identifies a significant asymmetric market response. Negative NIFTY 50 returns generate a stronger India VIX response than comparable positive returns, with the negative-return response approximately 1.79 times as large in magnitude. This may reflect heightened investor fear, increased demand for downside protection and reassessment of risk during declining markets. However, the asymmetry should not be attributed solely to irrational investor behaviour, as India VIX may also capture rational risk expectations, hedging demand and volatility risk premia.

Interestingly, the VIX × COVID interaction is statistically insignificant, indicating that although India VIX and market volatility reached exceptionally high levels during the pandemic, their predictive relationship was not significantly stronger during the specified COVID-19 period. Thus, extreme market conditions increased the *level* of uncertainty without producing statistically significant evidence of a stronger VIX–future volatility relationship.

The forecasting results further establish the practical relevance of India VIX. Incorporating VIX-implied variance into the GARCH-X model reduces out-of-sample variance MSE by approximately 7.70% and improves QLIKE relative to conventional GARCH(1,1). India VIX therefore provides useful incremental information for volatility forecasting rather than merely describing contemporaneous market uncertainty.

Overall, the evidence supports the use of India VIX as a complementary forward-looking indicator of market risk. However, the findings concern volatility prediction rather than stock-return direction, trading profitability or causality. India VIX should therefore complement, rather than replace, conventional historical-volatility measures and risk models.

VI. Conclusion

This study examined the predictive relationship between India VIX and NIFTY 50 realized volatility using daily NSE data from January 2015 to July 2026. The results show that India VIX significantly predicts subsequent 22-day realized volatility and retains its predictive power after controlling for preceding market volatility.

The findings also reveal a significant asymmetric response, with negative NIFTY 50 returns producing a stronger VIX response than comparable positive returns. However, the predictive relationship between India VIX and realized volatility was not significantly stronger during the specified COVID-19 period. Further, incorporating India VIX-implied variance into a GARCH-X model improved out-of-sample forecasting, reducing variance MSE by approximately 7.70% compared with conventional GARCH(1,1).

Overall, H1, H2, H3 and H5 are supported, while H4 is not supported. The study concludes that India VIX is a useful complementary and forward-looking indicator of market risk in the Indian equity market, although its predictive relationship should not be interpreted as evidence of causality or as a direct trading signal.

Future research may extend the analysis using alternative volatility models, intraday data and structural-break or regime-switching approaches.

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