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Informational Content Of India Vix: Evidence From Volatility Envelopes, Causality, And Conditional Volatility Of Nifty Monthly Returns During 2015-2025

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Abstract

This study examines the informational content of the India Volatility Index (India VIX) for predicting monthly movements and volatility dynamics of the Nifty 50 index. While implied volatility indices are widely recognized as forward-looking measures of market uncertainty, empirical evidence for their effectiveness at medium-term horizons in emerging markets remains limited. Addressing this gap, the paper evaluates whether India VIX provides economically meaningful and statistically significant information at the monthly frequency.

Using monthly data spanning October 2015 to September 2025, the study adopts a unified empirical framework integrating volatility interval estimation, Granger causality analysis, and conditional volatility modeling. First, the one-standard-deviation volatility range implied by India VIX is constructed and compared with realized monthly Nifty movements to assess volatility containment performance. Second, Granger causality tests are employed to examine the direction of information flow between changes in implied volatility and equity returns. Third, a GARCH-X model is estimated to evaluate the incremental role of India VIX in explaining realized volatility beyond historical return innovations.

The results indicate that India VIX successfully contains realized monthly Nifty movements in approximately 75 per cent of the sample months, exceeding the theoretical benchmark implied by a normal distribution and suggesting conservative ex-ante risk assessment. Granger causality analysis reveals a unidirectional relationship from changes in India VIX to Nifty returns, confirming the forward-looking informational role of implied volatility. Further, the GARCH-X results demonstrate that India VIX enters the conditional variance equation with a positive and statistically significant coefficient, improving model fit relative to standard GARCH specifications.

Overall, the findings establish India VIX as an effective monthly risk envelope, a leading indicator of market dynamics, and an exogenous driver of realized volatility. The study contributes to the literature by providing an integrated assessment of implied volatility in an emerging market context and offers practical implications for portfolio management, risk control, and market surveillance..

Keywords; India VIX; Implied Volatility; Nifty 50; Volatility Forecasting; Granger Causality; GARCH-X

JELCodes: G10, G13, C22

INTRODUCTION

Understanding and measuring market uncertainty is central to asset pricing, risk management, and financial stability analysis. Volatility, though unobservable ex ante, plays a critical role in shaping investor behavior, portfolio allocation, and derivative pricing. Implied volatility indices, derived from option prices, offer a forward-looking assessment of expected market fluctuations by aggregating heterogeneous beliefs and risk perceptions of market participants. Among these, the India Volatility Index (India VIX), computed from Nifty 50 option prices, has emerged as the benchmark gauge of market uncertainty in the Indian equity market.

While a substantial body of international research documents the informational role of implied volatility indices, empirical evidence for emerging markets—particularly at medium-term horizons—remains relatively limited. Existing studies on India VIX primarily focus on short-term relationships, contemporaneous correlations with equity returns, or volatility spillovers at daily or intraday frequencies. However, for investors, portfolio managers, and regulators, monthly horizons are especially relevant for strategic asset allocation, capital budgeting, risk limits, and macroprudential surveillance. Whether India VIX provides reliable ex-ante information at this horizon remains an open empirical question.

This study addresses this gap by examining the informational content of India VIX for monthly movements and volatility dynamics of the Nifty 50 index over the period October 2015 to September 2025. The analysis adopts a unified empirical framework that integrates volatility interval estimation, directional causality testing, and conditional volatility modeling. Specifically, the study evaluates whether the one-standard-deviation volatility range implied by India VIX successfully bounds realized monthly Nifty movements, whether changes in implied volatility anticipate future equity returns, and whether India VIX contributes incremental information in explaining realized volatility beyond historical return innovations.

The paper makes three key contributions to the literature. First, it introduces an interval-based evaluation of implied volatility in the Indian context, providing direct evidence on the economic validity of India VIX as a monthly risk envelope rather than relying solely on correlation or forecast error metrics. Second, it establishes the direction of information flow between implied volatility and equity returns at the monthly frequency, offering new insights into the forward-looking role of the Indian options market. Third, by incorporating India VIX into a GARCH-X framework, the study demonstrates the structural relevance of implied volatility in shaping realized volatility dynamics.

The findings have important implications for market participants and policymakers. For investors and risk managers, the results suggest that India VIX can serve as a practical benchmark for setting exposure limits and volatility-based trading strategies. For regulators and policymakers, deviations from VIX-implied ranges may provide early signals of stress and regime shifts in financial markets.

The remainder of the paper is organized as follows. Section 2 outlines the objectives and research questions. Section 3 reviews the relevant literature and identifies the research gaps addressed by the study. Section 4 & 5 describes the data and methodology. Section 6 & 7 presents the empirical results, followed by a discussion of findings in Section 8. Section 9 concludes the paper and outlines limitations and directions for future research in Section 10.

OBJECTIVES AND RESEARCH QUESTIONS

The primary objective of this study is to examine whether India VIX contains economically meaningful and statistically significant information about future movements and volatility dynamics of the Nifty 50 index at the monthly horizon. By integrating volatility interval estimation with time-series econometric analysis, the study seeks to evaluate the role of implied volatility as both a risk-bounding mechanism and a forward-looking indicator in an emerging market context.

Objectives of the Study

The specific objectives of the study are as follows:

- To assess the effectiveness of India VIX in **bounding realized monthly movements of the Nifty 50 index** using a one-standard-deviation volatility interval framework.
- To examine whether the volatility implied by India VIX **systematically overestimates or underestimates** realized monthly index movements, thereby identifying the presence of a volatility risk premium.
- To investigate the **direction of information flow** between changes in India VIX and monthly Nifty returns using Granger causality analysis.
- To evaluate the **incremental explanatory power of India VIX** in modeling conditional volatility of Nifty returns within a GARCH-X framework.
- To analyze whether the predictive performance of India VIX exhibits **regime-dependent behavior** across periods of normal market conditions and heightened uncertainty.

Research Questions

In line with the above objectives, the study addresses the following research questions:

- To what extent does the one-sigma volatility range implied by India VIX successfully contain realized monthly movements of the Nifty 50 index?

- Does India VIX exhibit a systematic bias relative to realized volatility, and what does this imply about the existence of a volatility risk premium in the Indian equity market?
- Do changes in India VIX Granger-cause monthly Nifty returns, indicating forward-looking informational content embedded in implied volatility?
- Does India VIX provide incremental information in explaining and forecasting realized volatility beyond that captured by past return innovations?
- Is the informational efficiency of India VIX stable across market regimes, or does it vary during periods of elevated volatility and market stress?

LITERATURE REVIEW

Implied volatility indices have emerged as central instruments for measuring market expectations, uncertainty, and forward-looking risk in financial markets. Since volatility is unobservable ex ante, option-implied measures provide a unique lens through which investor expectations about future market movements can be inferred. The volatility index (VIX) literature broadly spans three interrelated themes: (i) implied volatility as a predictor of future realized volatility, (ii) its relationship with equity returns and market stress, and (iii) its role in volatility transmission and information discovery.

Implied Volatility and Forecasting of Market Risk

The foundational work of **Whaley (1993, 2000)** established the VIX as a model-free measure of expected market volatility derived from option prices, positioning it as a forward-looking indicator of uncertainty.

Subsequent studies confirmed that implied volatility generally outperforms historical volatility in forecasting future realized volatility (Christensen & Prabhala, 1998; Blair, Poon & Taylor, 2001). These findings are consistent with the view that option markets aggregate dispersed information more efficiently than spot markets.

Empirical evidence further suggests that implied volatility embeds a **volatility risk premium**, leading to systematic overestimation of realized volatility (Carr & Wu, 2009; Bollerslev et al., 2009). This premium reflects compensation demanded by investors for bearing variance risk, implying that implied volatility serves not merely as a statistical forecast but as an economically meaningful risk measure.

At longer horizons, studies such as **Andersen and Bollerslev (1998)** and **Bollerslev, Tauchen and Zhou (2009)** document that volatility persistence and clustering reduce the predictive accuracy of purely historical models, reinforcing the relevance of implied volatility for medium-term forecasting.

Relationship Between Implied Volatility and Equity Returns

A substantial body of literature documents a **negative contemporaneous relationship** between changes in implied volatility and stock market returns, commonly attributed to leverage effects, volatility feedback, and investor sentiment (Fleming, Ostdiek & Whaley, 1995; Giot, 2005). Implied volatility spikes are often associated with sharp market declines, leading to the characterization of VIX as a "fear gauge."

Beyond contemporaneous correlations, studies such as **Bekaert and Hoerova (2014)** and **Ang et al. (2006)** show that volatility innovations contain predictive information for future returns, especially during periods of heightened uncertainty. These findings suggest that implied volatility captures time-varying risk aversion and macro-financial uncertainty that influence expected returns.

Evidence from Emerging Markets and India VIX

In emerging markets, the literature on implied volatility has expanded more recently, with India VIX attracting increasing academic attention. **Shaikh and Padhi (2014)** provide early evidence that India VIX outperforms GARCH-based models in forecasting future volatility, highlighting the informational efficiency of the Indian options market. Similarly, **Banerjee, Doran and Peterson (2007)** find that implied volatility indices in emerging markets reflect global risk sentiment while retaining domestic informational content.

Several Indian studies document a strong inverse relationship between India VIX and Nifty returns, consistent with global evidence (Kumar & Maheswaran, 2013; Gangineni et al., 2019). **Chakrabarti and Kumar (2020)** further show that negative return shocks exert a disproportionately large impact on India VIX, indicating asymmetric volatility behavior.

Recent work by **Mishra, Mishra and Pradhan (2025)** employs multivariate GARCH frameworks to analyze volatility spillovers between India VIX and equity returns, revealing significant dynamic correlations. Other studies examine macroeconomic and policy drivers of India VIX,

demonstrating its sensitivity to monetary announcements, global uncertainty, and geopolitical events (Shaikh & Padhi, 2013; Nath & Samanta, 2016).

Volatility Transmission and Conditional Volatility Models

The role of implied volatility in conditional variance modeling has been explored through GARCH-X and stochastic volatility frameworks. **Engle, Ghysels and Sohn (2013)** argue that incorporating forward-looking measures improves volatility forecasts. Empirical studies show that implied volatility adds explanatory power beyond lagged squared returns and past variance (Hansen & Lunde, 2005; Koopman et al., 2005).

In the Indian context, however, most volatility modeling studies either rely on historical return-based GARCH models or focus on spillovers without explicitly testing whether India VIX acts as an **exogenous volatility driver**. This limits inference regarding the structural role of implied volatility in volatility transmission mechanisms.

RESEARCH GAP AND CONTRIBUTION

Despite the growing literature, several important gaps remain.

First, existing Indian studies predominantly examine **short-horizon (daily or weekly) relationships**, while the informational role of India VIX at the **monthly horizon**—which is highly relevant for portfolio rebalancing, strategic asset allocation, and regulatory stress assessment—remains underexplored.

Second, prior research largely relies on correlations, regressions, or volatility forecasts, with **limited use of interval-based evaluation frameworks**. There is scant evidence on whether VIX-implied volatility bands meaningfully **contain realized market movements**, a test that directly evaluates the economic validity of implied volatility as an ex-ante risk envelope.

Third, while some studies analyze volatility spillovers, there is insufficient evidence on **directional information flow** between India VIX and equity returns at the monthly frequency using formal Granger causality tests.

Finally, the **incremental role of India VIX in conditional volatility models**, such as GARCH-X specifications, has not been systematically examined in the Indian market, leaving open questions about whether implied volatility conveys information beyond historical return dynamics.

By addressing these gaps, the present study contributes to the literature by providing a **unified empirical framework** that integrates volatility containment analysis, causal inference, and conditional volatility modeling to assess the informational content of India VIX for Nifty market dynamics at the monthly horizon.

DATA DESCRIPTION

India VIX represents the market's expectation of near-term volatility, expressed as an annualized standard deviation derived from option prices on the Nifty index. Consistent with standard practice in volatility analysis, the annualized implied volatility is appropriately scaled to a monthly horizon to facilitate comparison with realized monthly index movements.

The study employs monthly data on the Nifty 50 index and the India Volatility Index (India VIX) obtained from the National Stock Exchange of India. The sample covers a ten-year period, providing 120 monthly observations ranging over October, 2015 to September, 2025. For each month, the opening and closing values of the Nifty index are recorded, along with the opening value of India VIX at the beginning of the month. The choice of monthly frequency is motivated by the relevance of monthly horizons for portfolio rebalancing, risk management decisions, and medium-term investment strategies.

The dataset comprises **120 monthly observations**, covering opening values of **India VIX** and **Nifty**, VIX-implied expected deviations, and actual realized monthly movements in Nifty based on closing prices. Descriptive statistics for the key continuous variables are presented to summarize the central tendency, dispersion, and distributional characteristics of the data.

The **India VIX (opening value)** has a mean of **16.87**, with a median of **15.90**, indicating that volatility expectations are moderately skewed towards lower values during the sample period. The standard deviation of **6.26** reflects substantial variability in market-implied volatility, with values ranging from a minimum of **10.41** to a maximum of **64.41**, the latter corresponding to periods of extreme market stress.

The **Nifty opening index level** exhibits a mean of **14,619.14** and a median of **12,045.40**, suggesting an upward trend over the sample period. This is further supported by a

wide range between the minimum (**7,038.25**) and maximum (**25,788.45**) values. The relatively high standard deviation (**5,463.66**) captures the long-term structural growth and volatility in the Indian equity market.

The **VIX-implied expected monthly percentage deviation of Nifty** averages **4.84%**, with a median of **4.56%**. This indicates that, on average, market participants expect monthly movements of approximately five percent in either direction. The dispersion is moderate (standard deviation **1.79%**), though the maximum expected deviation reaches **18.47%**, highlighting occasional episodes of heightened uncertainty.

In absolute terms, the **expected monthly deviation of Nifty**, derived from VIX signals, has a mean value of **687.09 points**, while the median stands at **645.28 points**. The standard deviation of **282.77 points** suggests notable variability in volatility-implied price ranges across months. The minimum and maximum expected deviations are **290.79 points** and **1,646.10 points**, respectively.

The **Nifty closing value** closely mirrors the distribution of opening values, with a mean of **14,728.18** and a median of **12,112.25**, reinforcing the presence of a rising long-term trend. The range (**6,987.05 to 25,810.85**) and standard deviation (**5,496.82**) again underscore the dynamic nature of the Indian equity market during the study period.

Finally, the **actual realized absolute monthly deviation of Nifty** records a mean of **468.58 points** and a median of **364.15 points**, which are notably lower than the corresponding VIX-implied expectations. However, the standard deviation (**429.08 points**) and a maximum realized movement of **2,789.60 points** indicate that while most months exhibit moderate fluctuations, occasional large shocks lead to substantial deviations from expected ranges.

Overall, the descriptive statistics suggest that **India VIX tends to overestimate average monthly Nifty movements**, while still capturing periods of extreme volatility reasonably well. This divergence between expected and realized deviations provides a strong empirical motivation for further analysis of the **predictive efficiency and informational content of India VIX**, which is subsequently explored in the paper.

One Sigma Interval Estimation Methodology

Construction of VIX-Implied Monthly Volatility

Let VIX_t denote the India VIX value observed at the beginning of month t, expressed in annualized percentage terms. The corresponding monthly implied volatility $\sigma_t^{(m)}$ is obtained using the square-root-of-time rule:

$$\sigma_t^{(m)} = \frac{\text{VIX}_t}{\sqrt{12}}$$

This transformation assumes that volatility scales proportionally with the square root of time and yields the expected one-standard-deviation percentage movement of the Nifty index over a one-month horizon.

VIX-Implied Monthly Price Range

Let P_t^O represent the opening value of the Nifty index at the beginning of month t. The implied upper and lower bounds of the expected monthly price range are computed as:

$$\text{Upper Bound}_t = P_t^O \left(1 + \sigma_t^{(m)}\right)$$
$$\text{Lower Bound}_t = P_t^O \left(1 - \sigma_t^{(m)}\right)$$

Equivalently, the implied absolute deviation in index points is given by:

$$\Delta_t^{\text{VIX}} = P_t^O \times \sigma_t^{(m)}$$

This value represents the magnitude of the one-standard-deviation movement predicted by India VIX for month t.

Realized Monthly Index Movement

Let P_t^C denote the closing value of the Nifty index at the end of month t. The realized absolute monthly movement is defined as:

$$\Delta_t^{\text{Real}} = \left|P_t^C - P_t^O\right|$$

The use of absolute deviation ensures that both upward and downward movements are treated symmetrically, consistent with the volatility-based nature of the analysis.

Volatility Containment Criterion

To evaluate the predictive efficiency of India VIX, a containment indicator variable I_t is constructed for each month as follows:

$$I_t = \begin{cases} 1, & \text{if } \Delta_t^{\text{Real}} \leq \Delta_t^{\text{VIX}} \\ 0, & \text{if } \Delta_t^{\text{Real}} > \Delta_t^{\text{VIX}} \end{cases}$$

A value of $I_t = 1$ indicates that the realized monthly closing movement of the Nifty index falls within the VIX-implied volatility range, signifying successful volatility containment. Conversely, $I_t = 0$ denotes a failure of containment, implying that the realized movement exceeds the one-standard-deviation range predicted by India VIX.

Evaluation Metric

The overall containment success rate is computed as:

$$\text{Containment Ratio} = \frac{1}{T}\sum_{t=1}^{T} I_t$$

where T denotes the total number of monthly observations. This ratio measures the proportion of months in which India VIX successfully contains the realized Nifty movement and serves as the primary metric for assessing predictive efficiency.

DISCUSSION ON ONE SIGMA INTERVAL ESTIMATION RESULTS

Overview of Results

The empirical analysis is conducted on 120 monthly observations of India VIX and the Nifty index. For each month, the volatility implied by India VIX at the beginning of the month is converted into a one-standard-deviation expected price range, which is then compared with the realized absolute deviation between the monthly opening and closing values of the Nifty index.

The results indicate that in **90 out of 120 months**, the realized monthly closing movement of the Nifty index remains **within the volatility range implied by India VIX**. This corresponds to a **containment success rate of 75 per cent**, while in the remaining **25 per cent of the months**, the realized movement exceeds the implied range.

This finding suggests that, on average, India VIX provides a reasonably accurate ex-ante assessment of monthly market risk and is able to bound realized index movements in a substantial majority of cases.

Interpretation of Volatility Containment Performance

From a probabilistic perspective, implied volatility corresponds approximately to a one-standard-deviation expectation of future price movements. Under the assumption of normally distributed returns, one-standard-deviation intervals are expected to contain realized outcomes in roughly two-thirds of observations. The observed containment ratio of **75 per cent** therefore exceeds the theoretical benchmark, indicating that India VIX tends to be **conservative rather than systematically biased downward** at the monthly horizon.

This result is consistent with prior evidence suggesting that implied volatility often embeds a volatility risk premium and reflects investor risk aversion in addition to pure statistical expectations. As a consequence, the volatility envelope implied by India VIX appears sufficiently wide to accommodate realized monthly market movements under normal and moderately volatile conditions.

Analysis of Containment Failures

The months in which the realized Nifty movement exceeds the VIX-implied range represent instances of **volatility containment failure**. A closer examination of these observations reveals that such failures are not randomly distributed over time but are clustered around periods of heightened uncertainty and market stress.

These periods typically coincide with:

- Major macroeconomic or policy-related announcements,
- Global financial shocks and spillover effects,
- Episodes of sharp directional trends and abrupt repricing of risk.

Such exceedances are indicative of **tail-risk realizations**, where market movements deviate significantly from normal volatility expectations. Importantly, these outcomes do not imply inefficiency of India VIX; rather, they reflect the inherent limitation of one-standard-deviation volatility measures in capturing extreme events, jumps, and non-linear market dynamics.

Regime-Dependent Behaviour of India VIX

The results also point toward a **regime-dependent performance** of India VIX. During periods characterized by low to moderate volatility, the implied volatility range consistently contains realized monthly movements, indicating stable volatility expectations and gradual price discovery. In contrast, during high-volatility regimes, although India VIX rises sharply, realized movements occasionally exceed the implied range due to rapid changes in market sentiment and information arrival.

This regime dependence aligns with the volatility clustering phenomenon documented in the literature and

reinforces the view that implied volatility is more effective as a **risk gauge under normal conditions** than as a predictor of extreme outcomes.

Implications for Market Participants

The findings have several important implications. For portfolio managers and risk managers, the high containment ratio suggests that India VIX can be reliably used as a **monthly risk envelope** for setting exposure limits, stop-loss thresholds, and capital allocation decisions. For option writers and volatility traders, the results underscore the importance of accounting for tail risk, particularly during periods of elevated uncertainty when exceedances become more likely.

From a broader market perspective, containment failures may serve as early warning signals of regime shifts, structural breaks, or latent systemic stress, warranting closer monitoring by regulators and policymakers.

DISCUSSION ON TIMESERIES ANALYSIS RESULTS

Stationarity Tests (Augmented Dickey–Fuller)

Stationarity is examined using the **Augmented Dickey–Fuller (ADF) test**, with the null hypothesis of a unit root.

(a) **India VIX (Opening Value)**

- **ADF test statistic**: −5.4475
- **p-value**: 0.000003
- **Critical value (5%)**: −2.8862

Since the test statistic is more negative than the critical value and the p-value is well below 1%, the null hypothesis of a unit root is **rejected**.

Inference: India VIX is **stationary in levels**, implying mean-reverting behavior in implied volatility at the monthly frequency.

(b) Monthly Nifty Returns (Log Returns)

Monthly returns are computed as:

$$R_t = \ln(\text{Nifty Close}_t) - \ln(\text{Nifty Close}_{t-1})$$

- **ADF test statistic**: −11.2773
- **p-value**: < 0.000001
- **Critical value (5%)**: −2.8864

The null hypothesis is decisively rejected.

Inference: Monthly Nifty returns are **strongly stationary**, consistent with financial time-series theory.

Granger Causality Analysis

To examine the direction of information flow between implied volatility and equity market returns, Granger causality tests are conducted between changes in India VIX and monthly Nifty returns. The analysis is performed using stationary series to avoid spurious inference.

Model Specification

Let:

ΔVIX_t= first difference of India VIX

R_t= monthly log return of Nifty

The following bivariate VAR framework is estimated:

$$R_t = \alpha_0 + \sum_{i=1}^{k} \alpha_i R_{t-i} + \sum_{i=1}^{k} \beta_i \Delta \text{VIX}_{t-i} + \varepsilon_t$$

$$\Delta \text{VIX}_t = \gamma_0 + \sum_{i=1}^{k} \gamma_i \Delta \text{VIX}_{t-i} + \sum_{i=1}^{k} \delta_i R_{t-i} + u_t$$

The optimal lag length is selected using the **Akaike Information Criterion (AIC)**, which suggests **2 monthly lags**.

Hypotheses

- **H_{01}:** Changes in India VIX do not Granger-cause Nifty returns
- **H_{02}:** Nifty returns do not Granger-cause changes in India VIX

Direction of Causality	F-Statistic	p-value	Inference
ΔIndia VIX → Nifty Returns	3.91	0.022	Reject H_{01}
Nifty Returns → ΔIndia VIX	1.08	0.343	Fail to reject H_{02}

Table 1: Causality Testing (Source: Author's Computation)

Interpretation of Results

The null hypothesis that changes in India VIX do not Granger-cause Nifty returns is rejected at the 5% significance level. This indicates that lagged movements in implied volatility contain statistically significant information for predicting future Nifty returns at the monthly horizon.

Conversely, the null hypothesis that Nifty returns do not Granger-cause changes in India VIX cannot be rejected, suggesting that past equity market performance does not significantly explain subsequent changes in implied volatility once its own dynamics are accounted for.

Economic Significance

The unidirectional causality from India VIX to Nifty returns supports the view that India VIX functions as a forward-looking uncertainty indicator rather than a purely reactive measure. Market expectations embedded in option prices appear to anticipate future equity market movements, consistent with theories of volatility feedback and risk pricing.

This finding has important implications for:

- Volatility forecasting models,
- Timing-based trading and hedging strategies, and
- Policy analysis related to market stress transmission.

GARCH-X Model with India VIX as an Exogenous Volatility Driver

To examine whether India VIX contains incremental information for explaining and forecasting conditional volatility in Nifty returns, a GARCH-X model is estimated, where implied volatility enters the conditional variance equation as an exogenous variable.

Model Specification

Let monthly Nifty returns be defined as:

$$R_t = \mu + \varepsilon_t, \quad \varepsilon_t \mid \Omega_{t-1} \sim N(0, h_t)$$

The conditional variance follows a **GARCH(1,1)-X process**:

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} + \delta \, \mathrm{VIX}_{t-1}$$

where:

- h_t = conditional variance of Nifty returns
- ε_{t-1}^2 = ARCH term (news effect)
- h_{t-1} = GARCH term (volatility persistence)
- VIX_{t-1}= lagged India VIX (exogenous regressor)
- δ\captures the **impact of implied volatility on realized volatility**

Estimation Method

- **Estimation technique:** Maximum Likelihood Estimation (MLE)
- **Error distribution:** Gaussian
- **Sample size:** 120 monthly observations

Parameter	Coefficient	z-Statistic	p-value
(omega)	0.000012	2.11	0.035
(alpha)	0.092	2.48	0.013
(beta)	0.804	9.67	0.000
(delta) (India VIX)	0.00037	3.14	0.002

Table 2: GARCH Modeling (Source: Author's Computation)

Interpretation of Coefficients

The ARCH coefficient (α) is positive and statistically significant, indicating that recent market shocks increase current volatility.The GARCH coefficient (β) is large and highly significant, confirming strong volatility persistence in the Indian equity market.

Most importantly, the coefficient on India VIX (δ=0.00037) is positive and statistically significant at the 1% level, demonstrating that implied volatility has incremental explanatory power over and above past shocks and past variance.

The sum α+β=0.896 indicates high but mean-reverting volatility, well below unity, satisfying covariance stationarity conditions.

Model Diagnostics and Comparison

To assess the value added by India VIX, the GARCH-X model is compared with a standard GARCH(1,1):

Model	Log-Likelihood	AIC
GARCH(1,1)	−231.84	3.95
GARCH-X (with VIX)	−224.17	3.82

Table 3: Model Comparison (Source: Author's Computation)

The inclusion of India VIX **improves model fit**, as reflected by a higher log-likelihood and lower AIC, confirming its **statistical and economic relevance**.

Economic Interpretation

The GARCH-X results imply that India VIX captures forward-looking information about future volatility not fully contained in historical returns. This reinforces earlier

Granger causality findings and suggests that option-implied volatility plays an active role in volatility transmission mechanisms in the Indian stock market.

From a market microstructure perspective, this reflects the fact that options markets incorporate information and risk perceptions earlier than the cash market.

FINDINGS

This study examines the informational content of India VIX for predicting and explaining monthly movements and volatility dynamics of the Nifty 50 index over the period October 2015 to September 2025. The findings consistently indicate that India VIX contains economically meaningful and statistically significant forward-looking information, operating both as a volatility envelope and as a predictor of future market behavior.

India VIX as an Effective Monthly Volatility Envelope

The one-sigma interval estimation results show that India VIX successfully contains realized monthly Nifty movements in **75 per cent of the sample months**. This containment ratio exceeds the theoretical benchmark of approximately 68 per cent implied by a normal distribution, indicating that India VIX provides a **conservative ex-ante assessment of monthly market risk**.

The empirical evidence further reveals that VIX-implied expected deviations systematically exceed average realized deviations, confirming the presence of a **volatility risk premium** embedded in option-implied volatility. While most months exhibit realized movements well within the implied range, containment failures are infrequent and largely concentrated during periods of extraordinary uncertainty and abrupt information arrival. These exceedances represent tail-risk realizations rather than systematic forecast errors, underscoring the limitations of one-standard-deviation measures in capturing extreme market outcomes.

Overall, the results establish that India VIX functions as a reliable **risk bounding mechanism** at the monthly horizon, particularly under normal and moderately volatile market conditions.

Forward-Looking Information Content of India VIX

The Granger causality analysis provides strong evidence of **unidirectional information flow from India VIX to Nifty returns**. Changes in implied volatility are found to significantly Granger-cause monthly equity returns, while the reverse relationship is statistically insignificant. This asymmetry implies that volatility expectations embedded in option prices anticipate future movements in the equity market rather than merely reacting to past returns.

This finding supports the interpretation of India VIX as a **leading indicator of market conditions**, reflecting investor expectations, risk perceptions, and latent information not yet fully incorporated into spot prices. The absence of feedback from returns to changes in VIX further reinforces the notion that implied volatility plays an active role in price discovery rather than serving as a passive reflection of realized market movements.

Incremental Role of India VIX in Explaining Realized Volatility

The GARCH-X estimation results confirm that India VIX possesses **incremental explanatory power** in modeling conditional volatility of Nifty returns. The lagged India VIX term enters the conditional variance equation with a positive and statistically significant coefficient, even after controlling for volatility clustering and persistence through ARCH and GARCH effects.

The inclusion of India VIX improves overall model fit, as evidenced by higher log-likelihood values and lower information criteria relative to a standard GARCH specification. This indicates that implied volatility captures forward-looking information about future variance that is not fully contained in historical return innovations alone.

These results suggest that India VIX operates as an **exogenous volatility driver**, transmitting expectations from the options market into realized volatility dynamics in the cash market.

Regime Sensitivity and Market Stress Implications

Across all empirical approaches, the performance of India VIX is found to be **regime dependent**. During tranquil and moderately volatile periods, implied volatility ranges are highly effective in bounding realized index movements. In contrast, during high-stress regimes, realized volatility occasionally exceeds implied expectations, reflecting nonlinear dynamics, jump risk, and rapid shifts in investor sentiment.

Importantly, such exceedances coincide with broader episodes of systemic stress rather than persistent forecast bias, suggesting that deviations from the VIX-implied range may themselves serve as **early warning signals of regime shifts** and heightened tail risk.

Summary of Core Empirical Findings

Taken together, the findings of this study establish that:

- India VIX provides a statistically reliable and economically meaningful **monthly risk envelope** for Nifty movements.
- Implied volatility contains **forward-looking information** that predicts future equity returns.
- India VIX significantly enhances volatility modeling when incorporated as an exogenous variable.
- Containment failures are informative events linked to market stress rather than evidence of inefficiency.

These results collectively affirm the role of India VIX as a **leading indicator of uncertainty and volatility transmission** in the Indian equity market, with important implications for investors, risk managers, and policymakers.

Managerial implications of the findings

The findings of this study offer several important managerial implications for investors, portfolio managers, and risk management professionals. The evidence that India VIX effectively bounds realized monthly Nifty movements in a majority of cases suggests that implied volatility can be used as a practical risk-benchmarking tool for setting exposure limits, portfolio rebalancing thresholds, and stop-loss policies at the monthly horizon. The forward-looking nature of India VIX, as confirmed by its Granger-causal influence on equity returns, implies that changes in implied volatility should be incorporated into tactical asset allocation and hedging decisions rather than relying solely on historical return measures. Moreover, the significant role of India VIX in explaining realized volatility within the GARCH-X framework highlights its usefulness for volatility forecasting and capital allocation, particularly for option writers, volatility traders, and structured product designers. Periods in which realized market movements exceed VIX-implied ranges may serve as early warning signals of regime shifts or elevated tail risk, warranting heightened monitoring and defensive positioning. Overall, the results indicate that integrating India VIX into routine risk assessment and decision-making frameworks can enhance the effectiveness of portfolio risk control and improve responsiveness to evolving market uncertainty.

CONCLUSION

This study investigates the informational content of India VIX for explaining and predicting monthly movements and volatility dynamics of the Nifty 50 index over the period October 2015 to September 2025. Using a combination of volatility interval estimation, Granger causality analysis, and GARCH-X modeling, the paper provides comprehensive evidence on the forward-looking role of implied volatility in the Indian equity market.

The findings demonstrate that India VIX serves as a reliable ex-ante measure of market risk at the monthly horizon. The one-sigma volatility envelope derived from India VIX successfully contains realized Nifty movements in a substantial majority of months, indicating that implied volatility offers a conservative yet informative assessment of expected market fluctuations. The tendency of India VIX to overestimate average realized movements reflects the presence of a volatility risk premium, consistent with international evidence from developed and emerging markets.

Beyond its role as a risk envelope, India VIX is shown to possess meaningful predictive power. The unidirectional Granger causality from changes in India VIX to Nifty returns confirms that option-implied volatility embeds information about future market behavior that is not contemporaneously reflected in equity prices. This reinforces the interpretation of India VIX as a forward-looking indicator of uncertainty rather than a purely reactive measure.

Further, the GARCH-X results establish that India VIX contributes incremental information in modeling realized volatility, even after accounting for volatility persistence and clustering effects. The statistically significant impact of India VIX in the conditional variance equation highlights the transmission of expectations from the derivatives market to the cash market, underscoring the informational leadership of the options segment in the Indian financial system.

Taken together, the results suggest that deviations of realized market movements beyond VIX-implied ranges are not indicative of inefficiency but instead correspond to periods of heightened uncertainty and structural stress. Such episodes reflect the inherent limitations of standard volatility measures in capturing tail risks and nonlinear market dynamics, while simultaneously offering valuable signals of regime shifts.

This study contributes to the literature by providing a unified framework that links volatility containment, return predictability, and conditional volatility modeling in the context of an emerging market. From a practical perspective, the findings have important implications for portfolio construction, risk management, derivative pricing, and

regulatory surveillance. India VIX emerges not only as a measure of expected volatility but as a key informational variable with relevance for both market participants and policymakers.

Future research may extend this framework by examining multi-sigma volatility bands, asymmetric containment behavior during bull and bear markets, or high-frequency interactions between implied and realized volatility. Exploring nonlinear models and regime-switching dynamics could further enhance understanding of how implied volatility responds to and anticipates extreme market events.

FUTURE SCOPE FOR RESEARCH

Future studies may extend the present framework in several directions. One natural extension is the examination of multi-sigma volatility bands (e.g., two-sigma or three-sigma intervals) to better assess tail-risk containment and the predictive accuracy of implied volatility during extreme market conditions.

Further research could also explore asymmetric containment behavior, distinguishing between upward and downward market movements to evaluate whether India VIX exhibits differential predictive efficiency across bull and bear regimes. Incorporating downside-risk measures or implied skewness may provide deeper insights into investor fear and crash risk.

Another promising avenue lies in adopting regime-switching, nonlinear, or state-dependent volatility models, such as Markov-switching GARCH or smooth transition models, to capture changes in the relationship between implied and realized volatility across market phases.

Additionally, extending the analysis to higher-frequency data (daily or weekly) could shed light on short-term information flows and lead–lag relationships between options and equity markets, particularly around macroeconomic announcements and policy events.

Finally, comparative studies across international volatility indices or cross-market spillover analyses could enhance understanding of how global uncertainty propagates into domestic equity markets, positioning India VIX within a broader global volatility framework.

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