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WHEN DOES TRADING VOLUME IMPROVE VOLATILITY FORECASTING? REGIME-DEPENDENT RETURN–VOLUME–VOLATILITY DYNAMICS IN THE INDIAN EQUITY MARKET

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ABSTRACT

This study investigates whether trading volume improves volatility forecasting in the Indian equity market and whether its predictive contribution varies across market regimes. Using 2,477 daily observations on the NIFTY index, India VIX and trading volume from 1 April 2015 to 28 March 2025, the study examines the dynamic relationship among market returns, trading activity and volatility. The empirical framework combines GARCH-based volatility modelling, Markov-switching regime identification, structural-break analysis and out-of-sample forecast evaluation. Particular attention is given to whether the informational content of trading volume remains constant across market conditions or becomes more relevant during periods of heightened uncertainty. The study contributes to the existing return–volume–volatility literature by integrating regime dependence directly into volatility forecasting rather than treating trading volume as a uniformly informative variable. It also distinguishes between in-sample explanatory power and genuine out-of-sample predictive usefulness. The findings are intended to provide practical insights for investors, portfolio managers, derivatives traders and risk managers by clarifying how trading activity may be incorporated into volatility assessment under different market conditions. More broadly, the study offers a regime-sensitive framework for understanding when trading volume is likely to provide incremental information for forecasting volatility in an emerging equity market.

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KEYWORDS: - Trading volume; volatility forecasting; NIFTY 50; India VIX; GARCH; Markov switching; regime dependence; information arrival; Indian stock market.

1.0 INTRODUCTION

Volatility forecasting is central to financial-market analysis because it influences portfolio allocation, risk management, derivatives pricing and hedging decisions. Conventional GARCH-type models primarily rely on past return shocks and lagged conditional variance, yet market volatility is ultimately driven by the arrival and interpretation of new information. This raises an important question: can trading activity provide additional information about future volatility beyond that contained in historical returns?

Trading volume has long been used as a proxy for information flow in financial markets. Under the Mixture of Distributions Hypothesis, trading volume and volatility respond jointly to changes in information arrival, whereas the Sequential Information Arrival Hypothesis suggests that information reaches investors gradually, creating lead–lag relationships among returns, volume and volatility. Lamoureux and Lastrapes (1990) showed that incorporating trading volume into a conditional-variance model reduced volatility persistence, indicating that volume contains information not fully captured by standard GARCH terms. Chen, Firth and Rui (2001) further demonstrated that the relationship among returns, volume and volatility differs across markets, suggesting that the underlying mechanism is not universal.

Evidence from India also confirms the importance of trading activity. Mahajan and Singh (2008) found that including trading volume in NIFTY volatility models reduced part of the estimated persistence and supported sequential information arrival. Jena and Dash (2014) showed that lagged trading volume and open interest improved volatility modelling in NIFTY index futures. More recent studies have emphasized asymmetry. Siddiqui and Roy (2019), using NIFTY 50, India VIX and trading volume, found that the relationships vary across quantiles, while Naik and Sethy (2022) documented asymmetric return–volume effects and a positive volume–volatility relationship in the Indian market. Saranya and Sudhamathi (2024) also reported that the interaction among implied volatility, index returns and trading volume is not uniform across market conditions.

Recent international evidence has moved beyond simple asymmetry toward explicit regime dependence. Wang et al. (2025), using a regime-switching framework for the Chinese stock market, found that the volume–volatility relationship differs across high- and low-volatility states. This suggests that the informational value of trading volume may depend on the prevailing market regime rather than remain constant over time.

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Against this background, the present study examines whether trading volume improves volatility forecasting in the Indian equity market and whether its predictive contribution changes across market states. Using daily data on the NIFTY index, India VIX and trading volume from April 2015 to March 2025, the study compares conventional GARCH, volume-augmented GARCH and regime-dependent volatility models. It also evaluates their out-of-sample forecasting performance to determine whether trading volume provides genuine predictive gains rather than merely improving in-sample fit.

The study therefore focuses on the following central question:
When does trading volume improve volatility forecasting in the Indian equity market?

2.0 LITERATURE REVIEW

The relationship among stock returns, trading volume and volatility has been widely examined because trading activity may reflect the arrival and diffusion of new information in financial markets. Under the Mixture of Distributions Hypothesis, trading volume and volatility respond jointly to changes in information flow, whereas the Sequential Information Arrival Hypothesis suggests that information reaches investors gradually, creating lead–lag relationships among returns, volume and volatility.

Lamoureux and Lastrapes (1990) provided one of the earliest influential empirical demonstrations of this relationship by incorporating trading volume into a conditional-variance model. They found that volume significantly explained stock-return variance and reduced measured volatility persistence, supporting the view that trading activity can proxy information arrival. Chen, Firth and Rui (2001), using data from nine national markets, also reported a positive association between trading volume and the magnitude of price changes, although the direction of causal relationships differed across countries. This indicated that the return–volume–volatility nexus is not uniform across markets.

Later research increasingly focused on the predictive content of trading activity. Fleming and Kirby (2011) showed that trading volume and volatility exhibit substantial persistence and that innovation in the two series are strongly related. More recently, Maki (2024) demonstrated that asymmetric trading-volume measures can improve out-of-sample realized-volatility forecasts, suggesting that the effect of volume may depend on the nature of market activity rather than remaining constant over time.

Indian evidence similarly confirms a dynamic relationship among returns, volume and volatility. Singh and Balasubramanian (2000) reported lead–lag price–volume relationships consistent with sequential information arrival. Mahajan and Singh (2008), using NIFTY data and GARCH and

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EGARCH models, found that incorporating trading volume partly reduced volatility persistence and provided evidence that new information is incorporated into prices over time.

Evidence also suggests that these relationships are sensitive to market structure and market conditions. Mahajan and Singh (2013) showed that the return–volume relationship in India changed following the introduction of rolling settlement, indicating that trading and information-processing mechanisms may alter the underlying dynamics. Jena and Dash (2014), using NIFTY index futures, found that lagged trading volume and open interest contributed to volatility prediction, supporting the usefulness of trading-activity variables in GARCH-based models.

More recent studies emphasize asymmetry. Siddiqui and Roy (2019), examining NIFTY 50 returns, India VIX and trading volume, found that the relationships varied across quantiles and became stronger under more extreme market conditions. Naik and Sethy (2022) also documented asymmetric return–volume effects and a positive volume–volatility relationship in the Indian market, although volatility persistence remained substantial after volume was included in the model.

Saranya and Sudhamathi (2024) further examined the interaction among implied volatility, index returns and trading volume in India and reinforced the evidence that the relationships among these variables are not necessarily constant across market conditions.

The most recent international evidence has moved beyond simple asymmetry toward explicit regime dependence. Wang et al. (2025), using an endogenous regime-switching framework for the Chinese stock market, found that the volume–volatility relationship differed across high- and low-volatility regimes. Their findings indicate that trading volume may contain substantially different information depending on the prevailing market state.

Overall, the literature establishes that trading volume is closely related to market volatility and can contain predictive information beyond past returns. At the same time, the strength and direction of this relationship vary across markets, institutional settings, return distributions and volatility conditions. This evolving evidence provides the basis for examining the forecasting role of trading volume within a regime-dependent framework in the Indian equity market.

3.0 RESEARCH GAP

Existing studies have established significant relationships among stock returns, trading volume and volatility in both international and Indian markets. Indian research has examined these relationships using GARCH, EGARCH, Granger causality, quantile regression, India VIX and pre–post institutional comparisons. However, most studies assume that the informational effect

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of trading volume remains broadly constant across the sample or examine asymmetry without directly testing whether its forecasting usefulness changes across distinct volatility regimes.

Recent international evidence suggests that the volume–volatility relationship may be state dependent, with trading activity becoming more informative during high-volatility periods. Yet this regime-dependent forecasting perspective remains comparatively under-explored in the Indian cash-equity market.

Therefore, the present study addresses this gap by examining whether trading volume improves volatility forecasts differently across market regimes and by comparing conventional GARCH, volume-augmented GARCH and regime-dependent volatility models using out-of-sample forecasting performance.

4.0 RESEARCH OBJECTIVES

The study aims to:

1. Examine the dynamic relationship among NIFTY returns, trading volume and market volatility in the Indian equity market.
2. Identify distinct low- and high-volatility market regimes.

5.0 RESEARCH METHODOLOGY

5.1 Data and Sample

The study uses daily data from the Indian equity market covering the period from 1 April 2015 to 28 March 2025. The dataset contains 2,477 observations on the NIFTY index, India VIX and trading volume. NIFTY is used to represent market movements; India VIX captures forward-looking market uncertainty, and trading volume represents trading activity. Daily logarithmic returns are computed from successive NIFTY closing values. Trading volume is transformed into logarithmic form and, where required, differenced or detrended to improve stationarity and reduce the influence of long-term trends.

5.2 Preliminary Statistical Analysis

The analysis begins with descriptive statistics, including mean, standard deviation, minimum, maximum, skewness and kurtosis. The Jarque–Bera test is used to assess normality, while Pearson correlation coefficients provide an initial understanding of the relationships among NIFTY returns, absolute returns, India VIX and trading volume.

Stationarity is examined using the Augmented Dickey–Fuller (ADF) and KPSS tests. The ARCH-LM test is then applied to determine whether the return series exhibits conditional

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heteroskedasticity. Evidence of significant ARCH effects provides justification for the use of GARCH-family volatility models.

5.3 Dynamic Relationship and Causality

The short-run interactions among returns, trading volume and volatility are examined through a Vector Auto regression framework. Appropriate lag length is selected using standard information criteria such as the Akaike Information Criterion and Bayesian Information Criterion.

Granger-causality tests are used to assess whether past values of trading volume contain useful predictive information for returns or volatility, and whether returns or volatility, in turn, predict trading activity. Where appropriate, the Toda–Yamamoto causality procedure is applied as a robustness test, particularly when the variables exhibit different orders of integration.

5.4 Baseline Volatility Modelling

A standard GARCH (1,1) model is estimated as the benchmark volatility specification. The model captures the effects of recent return shocks and past conditional volatility on current market volatility. The degree of volatility persistence is assessed through the estimated ARCH and GARCH parameters.

This benchmark provides the basis for evaluating whether the inclusion of trading volume improves volatility modelling.

5.5 Volume-Augmented GARCH Model

The baseline GARCH model is extended by incorporating lagged trading volume into the conditional-variance specification. This allows the study to test whether trading activity provides additional information about future volatility beyond that contained in past return shocks and past volatility.

The statistical significance of the volume coefficient, changes in volatility persistence, model fit and information criteria are used to evaluate the contribution of trading volume.

5.6 Regime Identification

To account for possible changes in market behaviour, a two-state Markov-switching model is used to identify distinct low- and high-volatility regimes.

The model allows the mean and variance of returns to differ across market states and estimates the probability of remaining in or moving between the two regimes. This approach enables market regimes to be identified statistically rather than through arbitrarily selected event periods.

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A three-state specification may also be estimated as a robustness check and compared with the two-state model using information criteria.

5.7 Regime-Dependent Volume–Volatility Modelling

The central empirical model allows the effect of trading volume on volatility to differ between low- and high-volatility regimes.

Separate volume effects are estimated for the two market states. A statistically significant difference between these effects would indicate that the informational contribution of trading volume is regime dependent.

This specification directly addresses the main research question of whether trading volume improves volatility forecasting differently under changing market conditions.

5.8 Asymmetric Volatility Robustness

Because negative and positive return shocks may affect volatility differently, asymmetric volatility models such as EGARCH and GJR-GARCH are estimated as robustness checks.

These models allow the study to determine whether the principal findings remain valid after accounting for leverage and asymmetric volatility effects commonly observed in equity markets.

5.9 Structural-Break Analysis

As an additional robustness exercise, the Bai–Perron multiple structural-break test is employed to identify statistically significant changes in volatility dynamics or in the volume–volatility relationship over the sample period.

The Bai–Perron test is not used as the primary regime-identification method. Instead, it provides supplementary evidence on whether the underlying market relationship underwent structural changes during the study period and whether these changes broadly correspond with the regimes identified through the Markov-switching model.

5.10 Out-of-Sample Forecasting

To evaluate genuine predictive performance, the dataset is divided chronologically into an estimation sample and a holdout sample using an approximately 80:20 split.

One-step-ahead volatility forecasts are generated using three competing specifications:

1. Conventional GARCH,
2. volume-augmented GARCH,

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3. regime-dependent volume-augmented GARCH.

Forecast performance is evaluated using Mean Squared Error, Mean Absolute Error and QLIKE loss. Lower values indicate better forecasting accuracy.

The Diebold–Mariano test is used to determine whether differences in forecasting performance between competing models are statistically significant.

5.11 Model Diagnostics and Robustness Checks

The adequacy of the estimated volatility models is assessed through residual and specification diagnostics. These include:

- Ljung–Box tests on standardized residuals,
- Ljung–Box tests on squared standardized residuals,
- post-estimation ARCH-LM tests,
- Student-t error distribution,
- alternative regime specifications,
- alternative treatments of missing trading-volume observations,
- complete-case estimation,
- Alternative forecasting windows.

These tests are used to verify whether the main conclusions are robust to alternative model assumptions.

5.12 Model Selection

The competing models are evaluated using both in-sample and out-of-sample criteria.

In-sample performance is assessed through log-likelihood, Akaike Information Criterion, Bayesian Information Criterion and residual diagnostics. Out-of-sample performance is evaluated using MSE, MAE, QLIKE and Diebold–Mariano tests.

The preferred model is the specification that demonstrates satisfactory statistical diagnostics together with superior out-of-sample volatility-forecasting performance.

Empirical Results:

Baseline GARCH (1,1) Model

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Parameter / Test	**Result**	**Interpretation**
ARCH coefficient, α	**0.1111**	Recent shocks affect volatility
GARCH coefficient, β	**0.8580**	Strong persistence from past volatility
α + β	**0.9691**	Volatility is highly persistent
AIC	**6395.70**	Benchmark model fit
Ljung–Box, residuals, lag 10	**p = 0.091**	No significant residual autocorrelation at 5%
Ljung–Box, squared residuals, lag 10	**p = 0.568**	No significant remaining volatility dependence
Post-GARCH ARCH-LM	**p = 0.572**	Remaining ARCH effect not significant

Volume-Augmented GARCH-X Model

Parameter / Test	**Result**	**Interpretation**
Volume coefficient	**0.00363**	Positive volume effect
GARCH AIC	**6395.70**	Baseline
GARCH-X AIC	**6394.69**	Slight improvement
Likelihood-ratio statistic	**3.009**	GARCH vs GARCH-X
LR p-value	**0.0828**	Significant only at about 10%, not 5%

The baseline GARCH (1,1) model confirms strong volatility persistence in NIFTY returns. The estimated ARCH and GARCH coefficients are 0.1111 and 0.8580, respectively, giving a combined persistence value of 0.9691. This value, being close to unity, indicates that volatility shocks decay slowly over time. Residual diagnostic tests show no significant remaining serial correlation or ARCH effects, suggesting that the baseline model captures the major volatility dynamics reasonably well.

When trading volume is added to the standard GARCH specification, the volume coefficient is positive but only weakly significant. The likelihood-ratio test produces a p-value of 0.0828, while AIC improves only marginally from 6395.70 to 6394.69. This indicates that trading volume does not provide a strong and uniform incremental contribution to volatility when its effect is assumed to remain constant throughout the sample.

GJR-GARCH Asymmetry Test

Parameter / Test	**Result**	**Interpretation**
Asymmetry coefficient, γ	**0.1510**	Negative shocks have additional effect
z-statistic	**≈ 6.13**	Strong effect
p-value	**< 0.001**	Highly significant asymmetry
Standard GARCH AIC	**6395.70**	Benchmark

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GJR-GARCH AIC	**6341.75**	Clearly superior fit
Ljung–Box squared residuals	**p = 0.145**	No significant remaining dependence
Post-model ARCH-LM	**p = 0.142**	Remaining ARCH insignificant

GJR-GARCH with Trading Volume

Comparison	**Result**	**Interpretation**
GJR-GARCH AIC	**6341.75**	Without volume
GJR-GARCH-X AIC	**6339.56**	Better with volume
Likelihood-ratio statistic	**4.184**	Incremental volume contribution
p-value	**0.0408**	Significant at 5%

Student-t GARCH Robustness

Test / Criterion	**Result**	**Interpretation**
Estimated degrees of freedom	**≈ 6.36**	Heavy-tailed return distribution
Gaussian GARCH AIC	**6395.70**	Normal errors
Student-t GARCH AIC	**6265.72**	Much better model fit
GARCH vs Student-t	Student-t clearly better	Heavy tails matter
Student-t GARCH-X LR statistic	**1.607**	Volume addition
Volume LR p-value	**0.205**	Constant volume effect insignificant

The GJR-GARCH model reveals a strong asymmetric volatility effect. The asymmetry coefficient is positive and highly significant, with a p-value below 0.001. This implies that negative market shocks generate a greater increase in volatility than positive shocks of similar magnitude. The substantially lower AIC of the GJR-GARCH model also indicates that asymmetric volatility modelling is more appropriate than the conventional symmetric GARCH specification.

After accounting for asymmetric volatility, the addition of trading volume improves the model further. The likelihood-ratio test is significant at the 5% level, with a p-value of 0.0408, and the AIC declines from 6341.75 to 6339.56. This suggests that trading volume contains incremental information for volatility once the asymmetric response of volatility to market shocks is properly controlled.

The Student-t GARCH model provides a substantially better fit than the Gaussian GARCH model, as reflected in the much lower AIC. This confirms the heavy-tailed nature of NIFTY returns. However, adding trading volume to the Student-t specification does not produce a

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statistically significant improvement, with a likelihood-ratio p-value of 0.205. This again suggests that a constant volume effect is not robust across model specifications.

Two-State Markov-Switching Model

Measure	**Low-Volatility Regime**	**High-Volatility Regime**
Mean return	**0.0648%**	**−0.1950%**
Conditional variance	**0.5698**	**6.1677**
Approx. return SD	**0.755%**	**2.483%**
Share of observations	**≈92.3%**	**≈7.7%**
Mean India VIX	**≈15.92**	**≈28.83**
Mean trading volume	**≈311.01**	**≈494.94**
Probability of remaining in state	**0.9860**	**≈0.8629**

Two-State versus Three-State Markov Model

Model	**AIC**	**BIC**	**Preferred by IC?**
Two-state	**6431.07**	**6465.96**	No
Three-state	**6291.07**	**6360.85**	**Yes**

Characteristics of the Three Regimes

Regime	**Share**	**Mean Return**	**Return SD**	**Mean VIX**	**Mean Volume**
Calm	**56.2%**	**+0.131%**	**0.590%**	**14.33**	**285.0**
Normal	**42.0%**	**−0.067%**	**1.107%**	**19.09**	**363.6**
Extreme stress	**1.86%**	**−0.265%**	**4.537%**	**45.93**	**710.0**

The Student-t GARCH model provides a substantially better fit than the Gaussian GARCH model, as reflected in the much lower AIC. This confirms the heavy-tailed nature of NIFTY returns. However, adding trading volume to the Student-t specification does not produce a statistically significant improvement, with a likelihood-ratio p-value of 0.205. This again suggests that a constant volume effect is not robust across model specifications.

The three-state Markov model provides lower AIC and BIC values than the two-state model, indicating superior statistical fit. The three regimes can broadly be interpreted as calm, normal and extreme-stress states. However, the extreme-stress regime accounts for only about 1.86% of observations. Therefore, the two-state model remains preferable for the main analysis because of its greater parsimony and clearer interpretation, while the three-state model serves as a robustness check.

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Regime-Dependent Trading-Volume Effect

Parameter / Test	**Result**	**Significance**
Low-volatility volume coefficient, δL	**0.00950**	p = **0.302**
High-volatility volume coefficient, δH	**0.07666**	p = **0.0299**
Approx. δH / δL	**≈8.1 times**	Much larger in stress regime
Constant vs regime model LR statistic	**7.313**	—
LR p-value	**0.00685**	Highly significant
Student-t robustness LR	**6.218**	—
Student-t robustness p-value	**0.0126**	Significant

The regime-dependent model provides the strongest evidence in support of the study's central hypothesis. The trading-volume coefficient is not statistically significant during low-volatility periods, but becomes positive and significant during high-volatility periods. The high-volatility volume coefficient is approximately eight times larger than the low-volatility coefficient. The likelihood-ratio test strongly rejects the constant-volume specification, indicating that the influence of trading volume on volatility is significantly state dependent.

Out-of-Sample Forecasting Results

Item	**Value**
Training observations	**1,980**
Test observations	**496**
Training ends	**29 March 2023**
Forecast period begins	**31 March 2023**

Forecast Accuracy

Model	**MSE**	**MAE**	**QLIKE**
GARCH	**3.7558**	**0.7280**	**0.4133**
GARCH-X	**3.7396**	**0.7021**	**0.4122**
Regime-GARCH-X	**3.6896**	**0.6972**	**0.3962**

Improvement of Regime-GARCH-X over GARCH

Measure	**Improvement**
MSE	**≈1.76%**
MAE	**≈4.23%**
QLIKE	**≈4.15%**

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The out-of-sample forecast comparison shows that the regime-dependent GARCH-X model produces the lowest MSE, MAE and QLIKE values among the competing models. Relative to the standard GARCH model, it reduces MSE by approximately 1.76%, MAE by 4.23% and QLIKE loss by 4.15%. These results indicate that allowing the effect of trading volume to vary across market regimes improves volatility-forecasting accuracy.

Diebold–Mariano Forecast Compearison

Comparison	**Loss Measure**	**p-value**	**Interpretation**
GARCH vs GARCH-X	MSE	**0.250**	Not significant
GARCH vs GARCH-X	QLIKE	**0.878**	Not significant
GARCH vs Regime-GARCH-X	MSE	**0.0358**	**Significant at 5%**
GARCH vs Regime-GARCH-X	QLIKE	**0.0107**	**Significant at 5%**
GARCH-X vs Regime-GARCH-X	QLIKE	**≈0.088**	Significant at about 10%

For the key comparison:
- MSE-based DM statistic ≈ 2.10
- QLIKE-based DM statistic ≈ 2.55

The Diebold-Mariano tests show that the ordinary GARCH-X model does not significantly outperform the baseline GARCH model. In contrast, the regime-dependent GARCH-X model performs significantly better than standard GARCH under both MSE and QLIKE loss measures. This confirms that the forecasting benefit comes primarily from recognising regime dependence rather than simply adding trading volume to the variance equation.

Toda–Yamamoto Causality Test

Model specification:

Item	**Result**
BIC-selected lag length	**6**
Maximum integration order	**1**
Augmented VAR lag	**7**

Causality Results

Direction	**p-value**	**Conclusion**
India VIX → NIFTY return	**<0.001**	Strong causality
NIFTY return → India VIX	**<0.001**	Strong causality
Log volume → NIFTY return	**0.378**	Not significant
NIFTY return → Log volume	**0.620**	Not significant

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India VIX → Log volume	**0.031**	**Significant**
Log volume → India VIX	**0.0765**	Weak evidence at 10%

The causality analysis shows a strong bidirectional relationship between NIFTY returns and India VIX. Trading volume does not significantly predict signed NIFTY returns, nor do returns significantly predict trading volume. However, India VIX significantly predicts trading volume, while the reverse relationship is weakly significant. These findings suggest that trading activity is more closely associated with market uncertainty and volatility than with the direction of stock returns.

Bai–Perron Structural-Break Analysis

Using a 15% minimum segment length and BIC-based break selection:

Break	**Estimated Date**
Break 1	**14 December 2016**
Break 2	**6 March 2020**
Break 3	**15 September 2021**
Break 4	**14 March 2023**

BIC by Number of Breaks

Number of Breaks	**BIC**
0	**−1406.39**
1	**−1487.23**
2	**−1521.80**
3	**−1525.50**
4	**−1526.80**
5	**−1518.79**

The Bai-Perron structural-break analysis identifies four major break points in the sample: December 2016, March 2020, September 2021 and March 2023. The four-break specification produces the lowest BIC and is therefore preferred. The March 2020 break is particularly important because it corresponds closely with the onset of severe COVID-19 market stress. These findings provide additional evidence that the volume-volatility relationship is not structurally stable over the full sample period.

6.0 RESULTS & IMPLICATIONS

This study provides strong evidence that the forecasting value of trading volume in the Indian equity market is not constant across market conditions. Using daily NIFTY, India VIX and

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trading-volume data from April 2015 to March 2025, the analysis shows that market volatility is highly persistent, asymmetric and characterized by distinct low- and high-volatility regimes. More importantly, the role of trading volume changes materially across these regimes.

A conventional volume-augmented GARCH model produces only limited improvement over the standard GARCH specification, indicating that a single constant volume coefficient does not adequately capture the information contained in trading activity. In contrast, the regime-dependent model reveals that trading volume is not statistically important during low-volatility periods but becomes significantly more informative during high-volatility conditions. This result is reinforced by the likelihood-ratio tests and by the superior out-of-sample performance of the Regime-GARCH-X model.

The forecasting evidence is particularly important. The regime-dependent specification records the lowest MSE, MAE and QLIKE values, and Diebold–Mariano tests confirm statistically significant forecast improvements over the baseline GARCH model. Thus, the study demonstrates that the usefulness of trading volume lies not simply in its presence as an explanatory variable, but in when and under what market state that information is incorporated into volatility forecasts.

The results also have practical implications. For investors, risk managers and derivatives traders, trading volume should not be interpreted in isolation; its forecasting relevance increases substantially when market uncertainty is already elevated. For volatility modelling, this implies that regime-sensitive specifications may provide more informative risk estimates than conventional constant-parameter models.

7.0 CONCLUSION

The findings therefore make an important contribution to the Indian return–volume–volatility literature. They help explain why earlier studies have reported mixed evidence on the predictive role of trading volume: models that impose a constant relationship may average together fundamentally different market states. By allowing the volume–volatility relationship to vary across regimes, the present study uncovers a stronger and economically meaningful forecasting channel that is largely concentrated in high-volatility periods.

Trading volume improves volatility forecasting primarily when the market is under stress, and recognizing this regime dependence provides significantly better forecasts than treating the volume–volatility relationship as constant over time.

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This shifts the focus of the literature from asking whether trading volume matters to identifying when it matters most.

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