SECTOR ROTATION AND VOLATILITY REGIMES IN INDIA: THE ROLE OF INDIA VIX IN TIMING SECTOR ALLOCATION

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ABSTRACT

This study investigates whether India Volatility Index (India VIX) can serve as an effective timing indicator for volatility-driven sector rotation in the Indian equity market. Using daily data spanning 2009–2024 across eleven NSE sectoral indices, we employ fixed-effects panel regression, Vector Autoregression (VAR), Granger causality tests, and back-testing within a regime-classification framework. India VIX exhibits a statistically significant inverse relationship with sectoral returns ($\beta = -0.00063$, $p < 0.01$), a result that persists after controlling for the policy interest rate. Granger causality tests establish a unidirectional predictive relationship: India VIX leads sectoral returns, not the reverse. Regime-based analysis reveals that cyclical sectors (Banking, Auto) outperform during low-volatility environments (VIX < 15), while defensive sectors (Pharma, FMCG) provide relative resilience when fear spikes (VIX > 25). A rules-based sector rotation strategy exploiting these regime-dependent patterns achieves a Sharpe ratio of 0.2987 versus 0.1142 for an equal-weighted passive benchmark—a 161.6% improvement—with particularly pronounced outperformance during the COVID-19 crisis and post-crisis recovery. The findings challenge the semi- strong form of market efficiency in an emerging-market context and offer a transparent, implementable framework for volatility-conscious sector allocation.

Keywords: India VIX; Sector Rotation; Volatility Regimes; Risk-Adjusted Returns; Emerging Markets; Panel Regression; Granger Causality

1. INTRODUCTION

Financial markets are dynamic systems characterized by alternating phases of stability and turbulence. In emerging economies such as India, volatility clustering has intensified over the past decade, driven by global capital flow reversals, domestic policy shocks, and exogenous disruptions of the magnitude observed during the COVID-19 pandemic. These conditions expose the limitations of static, buy-and-hold portfolio strategies, which assume stable correlations and predictable return distributions—assumptions routinely violated during stress episodes.

Sector rotation—the dynamic reallocation of capital across industry groups in response to shifting economic conditions—offers a theoretically motivated alternative. The underlying premise is straightforward: cyclical sectors such as banking, automobiles, and real estate tend to outperform during expansionary phases when credit growth and consumer confidence are elevated, whereas defensive sectors such as pharmaceuticals and fast-moving consumer goods (FMCG) exhibit resilience in downturns owing to inelastic demand. Successfully implementing rotation, however, requires a reliable, timely signal for regime transitions.

The India Volatility Index (India VIX), derived from NIFTY 50 options prices, provides a forward- looking measure of 30-day expected market volatility and is widely interpreted as a barometer of investor fear. Despite its pervasiveness in risk management and derivatives pricing, its potential as a systematic, rules-based timing tool for sector allocation remains largely unexplored in the academic literature, particularly within the Indian context where market microstructure, retail investor composition, and behavioral dynamics differ substantially from those of developed economies.

This paper addresses that gap through four interrelated objectives: (i) quantifying the relationship between India VIX and cross-sectional sectoral returns; (ii) establishing the lead–lag predictive structure between volatility and sector performance; (iii) characterizing regime-dependent sectoral behavior across distinct VIX regimes; and (iv) evaluating whether a rules-based VIX-triggered rotation strategy generates superior risk-adjusted outcomes relative to a passive benchmark.

The study makes several contributions. Empirically, it provides the first comprehensive panel-based investigation of India VIX as a sector-rotation timing tool across eleven NSE indices over a 15-year period encompassing multiple market cycles. Methodologically, it integrates Granger causality, regime classification, and portfolio back-testing into a unified framework. From a practitioner standpoint, it delivers transparent, implementable allocation rules observable in real time. Theoretically, the evidence of predictable VIX-return dynamics in an emerging market challenges the semi-strong efficient market hypothesis and reinforces behavioral finance arguments regarding sentiment-driven mispricing.

2. LITERATURE REVIEW

2.1 Volatility Dynamics and Implied Volatility Indices

The theoretical foundation for this study draws on decades of research into time-varying volatility. Black (1976) documented the asymmetric return-volatility relationship known as the leverage effect, subsequently formalised by Bollerslev's (1986) GARCH framework, which established that volatility clusters in time-series data rather than remaining constant. Fleming, Ostdiek, and Whaley (1995) demonstrated that implied volatility indices encapsulate forward-looking information about market uncertainty beyond what realized volatility measures capture. Whaley (2000) extended this insight, positioning the VIX as an investor 'fear gauge.' In the Indian context, Banerjee (2015) and Kumar (2012) confirmed India VIX's short-term predictive ability for equity returns using ARIMA and regression approaches, while Giot (2005) showed that extreme VIX readings reliably precede significant market movements in developed markets.

2.2 Sector Rotation and Market Timing

The concept that sector performance varies systematically across business cycle phases is well established. Copeland and Copeland (1999) provided early evidence that volatility-based signals enhance portfolio performance via rotation across asset classes. Stangl, Jacobsen, and Visaltanachoti (2009) demonstrated that business-cycle-aligned rotation generates abnormal returns. Within India, Verma and Singh (2019) confirmed that active sector switching outperforms passive strategies during volatile periods, while Jadhao and Bhattacharyya (2017) showed that entropy-derived volatility signals improve allocation efficiency. The macroeconomic determinants of Indian sectoral returns have been examined by Pandey (2010), who identified oil prices and exchange rates as significant drivers, and Tripathi and Kumar (2014), who highlighted the role of foreign institutional investment flows.

ISSN: 2349-6762
Peer Reviewed & Refereed Journal (IF: 7.56)
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2.3 Behavioral Finance and Regime-Based Approaches

Baker and Wurgler (2006) established that investor sentiment systematically influences cross-sectional returns, particularly for assets difficult to arbitrage. Ding, Mazouz, and Wang (2015) linked volatility-based trading profits to behavioral biases including overreaction and herding. In India, Paramanik and Kar (2019) and Raut and Das (2020) documented the role of news sentiment and behavioral biases in driving return patterns. Hamilton's (1989) regime-switching framework formalised the notion that financial markets operate in discrete states, a concept reinforced by Bekaert and Harvey's (1997) findings on distinct volatility patterns in emerging markets relative to developed economies.

2.4 Research Gap

Despite extensive individual literatures on volatility indices, sector rotation, and behavioral finance, few studies integrate these strands into a unified empirical framework for an emerging market. Critically, no published study uses India VIX systematically to design and back-test a sector rotation strategy across a comprehensive set of Indian sectoral indices over a multi-cycle horizon. This study bridges that gap.

3. DATA AND METHODOLOGY

3.1 Data

The study utilises daily closing data from January 2009 through December 2024—3,910 trading days— sourced from the National Stock Exchange (NSE) of India. The sample encompasses eleven major sectoral indices: NIFTY Bank, Auto, IT, Pharma, FMCG, Energy, Metals, Realty, PSU, Financial Services, and Media. India VIX is obtained directly from NSE. The policy interest rate (repo rate) is sourced from the Reserve Bank of India (RBI). Supplementary validation draws on Bloomberg and CMIE Prowess. The time horizon deliberately spans multiple market regimes, including the post-global financial crisis recovery, the 2016 demonetisation shock, and the 2020 COVID-19 crisis.

Sectoral returns are computed as daily logarithmic price relatives: $R_{i,t} = \ln(P_{i,t} / P_{i,t-1})$. Sectors are classified a priori into cyclicals (Bank, Auto, Metals, Realty, Financial Services) and defensives (Pharma, FMCG, IT, PSU, Energy) based on established business-cycle sensitivity. Volatility regimes are defined using India VIX thresholds: Low ($VIX < 15$), Medium ($15 \le VIX \le 25$), and High ($VIX > 25$).

3.2 Econometric Framework

Four analytical layers compose the empirical strategy.

First, stationarity is assessed using Fisher-type panel Augmented Dickey–Fuller (ADF) unit root tests, which pool evidence across the eleven sectoral return series and the India VIX series, enhancing statistical power relative to univariate tests.

Second, the impact of India VIX on sectoral returns is estimated via fixed-effects panel regression:

$$R_{i,t} = \alpha_i + \beta_1 \, VIX_t + \beta_2 \, Repo_t + \varepsilon_{i,t}$$

where α_i captures time-invariant sector-specific fixed effects. Two specifications are estimated: a baseline model including only India VIX, and an extended model adding the repo rate as a macroeconomic control. Fixed effects control for unobserved structural heterogeneity across sectors (e.g., regulatory environment, liquidity differences).

Third, a VAR(2) model is estimated treating India VIX and the panel-average sectoral return

ISSN: 2349-6762
Peer Reviewed & Refereed Journal (IF: 7.56)
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as jointly endogenous, enabling examination of the dynamic propagation of volatility shocks to sector performance. Block-exogeneity Wald tests are applied to test Granger causality in both directions.

Fourth, the strategy is evaluated via back-testing. On each trading day, the portfolio allocates equally to all cyclical sectors when VIX < 15, maintains its prior allocation when 15 ≤ VIX ≤ 25 (neutral regime, avoiding excessive turnover), and shifts equally to all defensive sectors when VIX > 25. This allocation is compared against an equal-weighted passive benchmark holding all eleven sectors daily. Performance is assessed using the Sharpe ratio, Sortino ratio, maximum drawdown, and daily mean returns. A proportional transaction cost of 0.10% per complete portfolio rebalancing is deducted to ensure practical realism.

4. EMPIRICAL RESULTS

4.1 Distributional Properties

Table 1 reports descriptive statistics for India VIX and the pooled sectoral return series. India VIX displays pronounced positive skewness (3.29) and extreme kurtosis (22.21), consistent with extended calm periods punctuated by sharp spikes during episodes of market stress. The Jarque–Bera statistic strongly rejects normality ($p < 0.001$). Sectoral returns similarly exhibit fat-tailed distributions (kurtosis = 7.55), confirming that standard normal-based models understate tail risk. These findings motivate the use of regime-based, non- linear analytical approaches.

Table 1: Descriptive Statistics – India VIX and Sectoral Returns

Statistic	India VIX	Sector Returns (All)
Mean	17.352	0.00277
Median	15.898	0.00300
Maximum	70.385	0.29837
Minimum	10.135	−0.19267
Std. Deviation	6.064	0.03304
Skewness	3.287	0.272
Kurtosis	22.211	7.551
Jarque–Bera (p)	143,261 (0.000)	6,710 (0.000)

Note: Statistics computed using daily data from January 2009 to December 2024. Jarque–Bera tests the null of normality; p-values reported in parentheses.

4.2 Unit Root Tests

Fisher-type panel ADF tests strongly reject the null hypothesis of unit roots for both India VIX (Fisher $Chi^2 = 443.74$, $p < 0.001$) and the sectoral return series (Fisher $Chi^2 = 1923.13$, $p < 0.001$). The confirmed stationarity of all series precludes spurious regression concerns and validates subsequent panel and VAR estimation.

4.3 Panel Regression: India VIX and Sectoral Returns

Table 2 presents fixed-effects panel regression results. In the baseline specification, the India VIX coefficient is negative and highly significant ($\beta = -0.00063$, $t = -10.09$, $p < 0.001$), indicating that a one-unit increase in India VIX is associated with an average decline of approximately 6.3 basis points in daily sectoral returns. The relationship is economically

ISSN: 2349-6762
Peer Reviewed & Refereed Journal (IF: 7.56)
Journal Website www.nrjbfm.in

meaningful: a VIX spike from 15 to 35 (as observed during acute crises) translates to an estimated return drag of roughly −126 basis points per day, compounding substantially over crisis duration.

In the extended model including the repo rate, India VIX retains statistical significance and its coefficient magnitude increases marginally ($\beta = -0.00068$). The repo rate itself exerts a significant negative effect ($\beta = -0.00141$, $p < 0.001$), consistent with the view that monetary tightening constrains equity performance through higher discount rates and reduced credit availability. Crucially, the retention of VIX significance after macroeconomic conditioning implies that India VIX captures a dimension of risk—plausibly investor sentiment and uncertainty aversion—that conventional economic variables do not fully subsume.

Table 2: Fixed-Effects Panel Regression of Sectoral Returns on India VIX

Variable	Baseline Model		Extended Model	
	Coeff.	p-value	Coeff.	p-value
Constant	0.01364***	0.000	0.02321***	0.000
India VIX	−0.00063***	0.000	−0.00068***	0.000
Repo Rate	—	—	−0.00141***	0.000
R^2	0.0133		0.0156	
F-statistic (p)	9.355 (0.000)		10.092 (0.000)	

Note: *** denotes significance at the 1% level. All models include sector fixed effects. Standard errors are cross-section SUR. Dependent variable is daily log sectoral return.

4.4 Granger Causality and VAR Dynamics

Table 3 reports block-exogeneity Wald test statistics from the VAR(2) system. The null that India VIX does not Granger-cause sectoral returns is decisively rejected ($\chi^2 = 28.33$, df = 2, $p < 0.001$). The reverse hypothesis—that returns Granger-cause India VIX—is not rejected ($\chi^2 = 0.874$, $p = 0.646$), establishing a clean, unidirectional predictive relationship. VAR coefficient estimates corroborate this structure: VIX(−1) loads negatively on returns ($\beta = -0.00188$, $t = -4.45$) and VIX(−2) loads positively ($\beta = 0.00214$, $t = 5.17$), consistent with delayed mean-reversion dynamics. Lagged returns, by contrast, are statistically inert in the VIX equation.

This unidirectionality is the critical result for the rotation strategy's economic validity. Investors can observe India VIX in real time and use it to anticipate, rather than merely react to, directional sector-return shifts.

Table 3: Granger Causality / Block Exogeneity Wald Tests (VAR System)

Dependent Variable	Excluded Variable	Chi²	df	p-value
Sectoral Returns	India VIX	28.333	2	0.000***
India VIX	Sectoral Returns	0.874	2	0.646

Note: VAR estimated with 2 lags selected by AIC. *** $p < 0.01$. The null hypothesis is that the excluded variable does not Granger- cause the dependent variable.

4.5 Volatility Regime-Dependent Sectoral Performance

Table 4 presents mean returns and standard deviations for selected sectors across high- and low-VIX regimes. During high-volatility periods (VIX > 25), aggregate sectoral returns average −0.46% per day. Cyclical sectors bear the brunt: NIFTY Bank and Auto record mean daily losses of −0.67% and −0.61% respectively, accompanied by substantially elevated return dispersion. NIFTY Pharma is the notable exception, posting a positive mean return (+0.41%) during high-VIX episodes, reflecting genuine defensive characteristics. NIFTY FMCG exhibits losses but these are modest (−0.19%) relative to cyclicals.

The pattern inverts sharply during low-volatility regimes (VIX < 15). Aggregate sectoral returns average +0.51% per day. Cyclical sectors lead, with Bank and Auto posting +0.49% and +0.47% respectively. Importantly, return volatility contracts markedly—standard deviations are two to three times lower than in high- VIX regimes—confirming that regime classification captures genuine state-dependent risk-return dynamics, not merely average effects.

Table 4: Sectoral Returns Across Volatility Regimes

Sector	High-VIX Mean	High-VIX Std.	Low-VIX Mean	Low-VIX Std.	Regime Shift
NIFTY Bank	−0.00669	0.0614	0.00492	0.0182	Cyclical
NIFTY Auto	−0.00609	0.0571	0.00468	0.0210	Cyclical
NIFTY FMCG	−0.00188	0.0307	0.00384	0.0184	Defensive
NIFTY Pharma	+0.00412	0.0407	0.00504	0.0237	Defensive
Aggregate	**−0.00459**	**0.0502**	**0.00506**	**0.0247**	—

Note: High-VIX regime: India VIX > 25. Low-VIX regime: India VIX < 15. All figures are daily averages over the respective regime observations.

4.6 Portfolio Back-Testing: VIX Rotation vs. Passive Benchmark

Table 5 consolidates strategy performance. Across the full 2009–2024 sample, the VIX-rotation portfolio more than doubles the passive benchmark's mean daily return (0.64% vs. 0.28%), while simultaneously reducing portfolio standard deviation (2.14% vs. 2.43%). The Sharpe ratio improves from 0.1142 to 0.2987, a 161.6% uplift. This improvement reflects not simply higher average returns but a fundamentally better risk-return trade-off achieved through systematic defensive repositioning during stress episodes.

The sub-period analysis provides particularly compelling evidence of the strategy's stress-resilience. During the COVID-19 crisis period, when both strategies suffer, the rotation approach limits damage by shifting to defensives as VIX surged above 70—the highest reading in the index's history. The strategy's Sharpe ratio during COVID (0.019) substantially exceeds what a static cyclical exposure would have produced. In the post- COVID recovery, the strategy captures the cyclical rebound as VIX normalised below 15, achieving a Sharpe ratio of 0.467.

Regime-wise analysis further shows that the best risk-adjusted outcomes materialise in medium-VIX conditions (Sharpe = 0.409), when the market exhibits directional movement without panic-driven dislocations. In high-VIX regimes, the rotation strategy still loses money on average but the losses are markedly smaller than a purely cyclical portfolio would sustain.

Table 5: Portfolio Performance – VIX Rotation vs. Buy-and-Hold Benchmark

Portfolio / Period	Mean Daily Return	Std. Deviation	Sharpe Ratio	Improvement
Buy-and-Hold (Full)	0.002773	0.02427	0.1142	—
VIX Rotation (Full)	**0.006391**	**0.02140**	**0.2987**	**+161.6%**
VIX Rotation – Pre-COVID	0.006285	0.01935	0.3247	
VIX Rotation – COVID	0.000486	0.02564	0.0190	
VIX Rotation – Post-COVID	0.010595	0.02269	0.4670	

Note: Transaction costs of 0.10% applied per portfolio rebalancing. Sharpe ratio computed using a risk-free rate of 4.5% annualised. Pre-COVID: Jan 2009–Dec 2019; COVID: Jan 2020–Dec 2021; Post-COVID: Jan 2022–Dec 2024.

5. DISCUSSION

5.1 Efficiency and the Predictive Content of India VIX

The Granger causality results present a direct challenge to the semi-strong form of the Efficient Market Hypothesis (EMH). Under EMH, publicly available information—including a real-time index such as India VIX—should be instantaneously impounded in prices, leaving no systematic exploitable relationship. The documented unidirectional predictive structure suggests instead a delayed adjustment mechanism: volatility signals propagate into sectoral prices with a measurable lag, plausibly due to limits to arbitrage, institutional capacity constraints, or the heterogeneous processing of risk information among market participants.

Alternatively, the strategy's outperformance may reflect compensation for bearing state-dependent risk rather than a pure efficiency violation. During high-VIX regimes, defensive positioning entails accepting the implicit risk of missing cyclical upswings if fear abates quickly; the Sharpe improvement may partly represent a risk premium for this timing uncertainty. Disentangling these explanations fully requires a multi-factor asset pricing decomposition—a direction we identify for future research.

5.2 Behavioral Dimensions

The finding that India VIX retains explanatory power net of the repo rate is consistent with Baker and Wurgler's (2006) sentiment-channel hypothesis: volatility indices embed collective investor psychology that extends beyond macroeconomic fundamentals. During high-VIX regimes, risk-averse and loss-averse investors may collectively flee cyclicals toward defensives, thereby amplifying the cross-sectional return divergence documented in Table 4. The rotation strategy effectively harvests this predictable behavioural pattern. The partial resolution of Hypothesis H4—that a full Fama–French multi-factor test was not conducted—is acknowledged as a limitation; the positive alpha demonstrated here may partially reflect exposure to documented risk factors (e.g., low-volatility, quality premia) rather than pure sentiment-driven mispricing.

5.3 Practical Considerations

Three practical dimensions merit discussion. First, the threshold values employed (VIX < 15, VIX > 25) are derived from historical distributional analysis. These thresholds may require recalibration as the structural volatility level of Indian markets evolves—for instance, if geopolitical integration raises the long-run mean of India VIX. Second, the transaction cost assumption of 0.10% per rebalancing is conservative but uniform; actual costs will vary with investor type, order size, and prevailing liquidity. Third, the strategy rebalances only when the VIX regime changes, not on a fixed schedule, minimising unnecessary turnover while remaining responsive to genuine state transitions.

6. CONCLUSION AND IMPLICATIONS

This study demonstrates that India VIX is not merely a passive measure of market anxiety but a forward-looking signal with exploitable predictive content for sector-level equity returns. Three principal findings emerge. First, India VIX exhibits a robust, negative association with sectoral returns that survives macroeconomic conditioning, confirming its role as a multi-dimensional risk indicator that captures sentiment beyond what conventional economic variables reflect. Second, the predictive relationship is unidirectional— VIX leads returns, not the reverse—validating its use as a leading indicator for tactical reallocation. Third, a transparent, rules-based rotation strategy exploiting these dynamics achieves a Sharpe ratio 161.6% higher than the equal-weighted passive benchmark, with particularly strong downside protection during the COVID-19 shock.

The theoretical implications are substantive. The findings challenge the informational efficiency of an important emerging market and support a behavioral interpretation in which volatility signals systematically precede price adjustments—consistent with rational inattention, limits to arbitrage, or sentiment-driven dynamics. The empirical evidence also extends the Arbitrage Pricing Theory by identifying India VIX as a meaningful priced risk factor at the sector level.

For portfolio managers, the strategy offers a concrete, implementable framework: observe India VIX daily, rotate into cyclicals when fear is low, pivot to defensives when fear spikes, and hold the prior allocation in intermediate regimes to limit transaction costs. For risk managers, India VIX thresholds provide early warning signals of sector-level stress. For regulators and policymakers, the results underscore that volatility sentiment in Indian markets can trigger cross-sectional capital reallocation with potential implications for financial stability.

Future research directions include: (i) extension to intraday or high-frequency VIX signals to assess whether finer temporal granularity improves timing precision; (ii) cross-country comparison across South Asian or BRICS emerging markets to assess generalisability; (iii) integration of machine-learning-based regime detection to identify non-linear VIX threshold structures; (iv) incorporation of India VIX derivatives as hedging overlays during high-volatility transitions; and (v) a comprehensive Fama–French multi-factor decomposition of the strategy's alpha to sharpen the efficiency versus risk-premium interpretation.

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