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Regime-Sensitive Sectoral Allocation and Downside Risk Analysis in the Indian Equity Market: Evidence from Markov Switching GARCH-X and CVaR Models

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ABSTRACT

This study Analyses volatility dynamics in India's Nifty 50 index using daily data from July 2011 to February 2026, revealing persistent clustering and distinct high/low volatility regimes via GARCH (1,1), GARCH-X (incorporating crude oil, gold, USDINR), and two-state Markov Switching models. Results show strong volatility persistence (sum $\alpha+\beta \approx 0.98$), regime stickiness (transition probabilities 0.94/0.97), and superior tail-risk capture by CVaR over VaR, with defensive sectors (FMCG, Pharma) showing lower downside exposure. Findings advocate regime-adaptive allocation—45% to defensives in high-vol states vs. growth sectors (Banking, IT) in stable periods—for enhanced risk-adjusted returns in emerging markets.

Index Terms — Indian equity market, Markov Switching, GARCH-X, CVaR, sector allocation, volatility modelling.

I. INTRODUCTION

The Indian equity markets, exemplified by the Nifty 50 benchmark, exhibit pronounced volatility clustering and abrupt regime shifts driven by domestic policy changes, global commodity shocks, and FII flows—necessitating models beyond constant-variance assumptions. Traditional GARCH frameworks capture time-varying risk but overlook structural breaks; this paper integrates GARCH-X (exogenous macros: oil/gold/exchange rates) with Markov Switching to detect persistent states and quantify sector-specific risks via VaR/CVaR.

While prior Indian studies confirm GARCH persistence in Nifty returns, few link macro drivers to regimes or propose actionable allocation rules. We address this gap by estimating downside risks across sectors (Banking, IT, FMCG, Pharma, Auto) and deriving a dynamic framework: overweight defensives during stress (e.g., 2020 crisis spikes) while rotating to cyclicals in calm phases. This contributes practical tools for portfolio managers navigating India's volatile landscape, where oil import dependence amplifies external shocks.

II. REVIEW OF LITERATURE

Volatility modeling in emerging markets like India reveals persistent clustering and regime shifts, foundational for dynamic sector allocation. Bollerslev's (1986) GARCH(1,1) captures time-varying variance via ARCH/GARCH terms near unity, widely applied to Nifty/Sensex data.

GARCH Applications in Indian Equities. Khera, Goyal, and Yadav (2022) analyzed sectoral volatility (2014–2019) using GARCH(1,1)/GARCH-M, finding ARCH effects in five sectors, highest persistence in Nifty Media, lowest in Realty—but symmetric models miss asymmetry. Karmakar (2005) modeled Nifty/Sensex conditional volatility (1991–2003), confirming clustering, persistence, predictability, with limited leverage effects urging asymmetric extensions. Mehta and Sharma (2011) evidenced GARCH clustering/persistence in Nifty (2001–2010) for forecasting. Singh and Ahmad (2011) favored TGARCH/PGARCH over standard GARCH for Nifty volatility. Yeasin et al. (2020) improved GARCH-X with macros (e.g., FX), boosting accuracy. Mathur, Chotia, and Rao (2015) highlighted crisis spikes (2001–2012 BSE), Nathani and Kushwah (2022) noted Nifty-Nasdaq spillovers.

Regime-Switching Models. Hamilton and Raj (2001) overviewed Markov Switching for cycles, extendable to GARCH. Guidolin (2011) reviewed its finance applications for states/forecasting. Haas, Mittnik, and Paolella (2004) advanced MS-GARCH for nonlinear dynamics/exchange rates. Savku and Weber (2020) applied to optimization under uncertainty.

Sector Allocation and Portfolio Optimization. Doeswijk and Van Vliet (2010) showed momentum/seasonals excel in global sectors (1970–2008). Bessler, Taushanov, and Wolff (2021) found factors outperform long-term, sectors in crises (2007–2020). Kalotychou, Staikouras, and Zhao (2014) boosted mean-variance via dynamic correlations/asymmetry. Gupta (2009) used asymmetric DCC-GARCH (1997–2007) for superior Nifty sector trade-offs.

Indian portfolios emphasize Sharpe Index/Treynor: Sandhar, Jain, and Kushwah (2018) selected NSE stocks (2010–2016), favoring undervalued ones. Lal and Subba Rao (2016) optimized NSE sectors (2014–2015). Rout et al. (2020) diversified NSE via beta. Sen and Dasgupta (2024) ranked MVP>autoencoders (2018–2022 NSE). Sen and Dutta (2023) preferred HRP>HERC (2016–2021). Saranya and Prasanna (2014) added skewness/kurtosis to Markowitz (2000–2011).

Statistical tools (ADF, JB, AIC) and software (rugarch, statsmodels) are standard.

Overall, literature confirms GARCH persistence, Markov regimes, and dynamic allocation benefits in India, but gaps remain in fusing GARCH-X macros, regime-filtered CVaR, and empirical sector weights for Nifty (Banking/IT vs. FMCG/Pharma/Auto). This study fills that with a four-stage framework (2011–2026), proposing adaptive strategies.

III. OBJECTIVES OF THE STUDY

The primary objective of the study is to examine how dynamic volatility regimes and downside risk measures can be used to improve sectoral allocation decisions in the Indian equity market.

The secondary objectives are as follows:

- To analyze the volatility behavior of the Nifty 50 and selected sectoral indices.
- To examine the effect of crude oil prices, gold prices, and exchange rate movements on market volatility using GARCH-X.
- To identify high-volatility and low-volatility market regimes using a Markov Switching model.
- To estimate downside risk through VaR and CVaR measures.
- To propose a regime-sensitive sector allocation strategy based on empirical findings.

IV. RESEARCH METHODOLOGY

This analysis employs a quantitative design using daily closing prices for Nifty 50 and sectoral indices (Banking, IT, FMCG, Pharma, Auto) sourced from the National Stock Exchange (NSE) database and Yahoo Finance, spanning July 19, 2011, to February 27, 2026 (n=3,623 observations post-cleaning for holidays/missing values). Macroeconomic inputs—WTI crude oil (USD/bbl), MCX gold (INR/10g), and USDINR spot rates—were obtained from Investing.com and RBI archives to match exact trading days.

Data preprocessing converts levels to continuously compounded log returns: $r_t = \ln(P_t/P_{t-1})$, ensuring stationarity confirmed via Augmented Dickey-Fuller tests (ADF p<0.01 across series). The four-stage framework proceeds as follows:

1. **Descriptive Analysis**: Jarque-Bera tests verify non-normality (JB>1,000, p<0.001); Ljung-Box Q(20) on squared residuals flags ARCH effects.

2. **Volatility Modeling**: Baseline GARCH(1,1) estimates conditional variance $h_t = \omega + \alpha\epsilon_{t-1}^2 + \beta h_{t-1}$, extended to GARCH-X: $h_t = \omega + \alpha\epsilon_{t-1}^2 + \beta h_{t-1} + \gamma_1 \mathrm{Oil}_t + \gamma_2 \mathrm{Gold}_t + \gamma_3 \mathrm{FX}_t$. Maximum likelihood via R's rugarch package; fit assessed by AIC (-5.24 vs. -5.12 baseline), BIC, and Q-residual diagnostics.

3. **Regime Detection**: Two-state Markov Switching model with transition probabilities $p_{ij} = P(S_t = j \mid S_{t-1} = i)$, estimated via Hamilton filter in Python's statsmodels. Regime persistence validated (high-vol: 0.94, low-vol: 0.97); likelihood ratio test rejects single-regime (p<0.001).

4. **Downside Risk**: Historical simulation computes 95% VaR/CVaR from empirical quantiles of regime-filtered returns, enabling sector rotation rules.

Robustness checks include rolling-window GARCH (60-day) and alternative distributions (Student-t, skewed-t). All code is reproducible via GitHub-supplement (appendix link).

V. RESULTS AND DISCUSSION

Empirical findings confirm pronounced volatility dynamics in Nifty 50 and sectoral returns, with GARCH models revealing strong persistence and Markov Switching identifying sticky regimes that guide adaptive allocation.

5.1 Descriptive Statistics

The descriptive statistics indicate that returns are non-normal and show excess kurtosis, which suggests the presence of fat tails and a higher probability of extreme outcomes. Sectoral volatility differs meaningfully across industries, with cyclical sectors generally showing higher standard deviation than defensive sectors.

The higher kurtosis values across all indices indicate the presence of extreme returns and fat tails, which is a common characteristic of financial time series. Among the sectors, the banking and IT indices exhibit higher standard deviation, reflecting their sensitivity to economic cycles and market sentiment. In contrast, FMCG and Pharma sectors show relatively lower volatility, reinforcing their defensive nature and stability during uncertain market conditions.

Table 1: Descriptive Statistics of Nifty 50 And Selected Sectoral Returns

Index	Mean Return	Std. Deviation	Skewness	Kurtosis	JB (p-val)	Interpretation
Nifty 50	0.0008	0.0123	0.45	8.72	<0.001	High volatility persistence
Bank	0.0011	0.0185	0.38	9.10	<0.001	More cyclical risk
IT	0.0009	0.0162	0.29	8.44	<0.001	Sensitive to market shifts
FMCG	0.0006	0.0094	0.21	6.95	<0.001	Defensive behavior
Pharma	0.0007	0.0101	0.26	7.31	<0.001	Lower downside risk
Auto	0.0008	0.0158	0.31	8.21	<0.001	Moderate-to-high cyclicality

Note: **$p<0.01$,** $p<0.05$, $p<0.1$ for mean t-tests vs. zero. Ljung-Box Q(20) on squared returns: all $p<0.001$ (ARCH effects)

5.2 GARCH and GARCH-X Results

The GARCH model confirms that current volatility depends strongly on past shocks and past volatility, reflecting volatility clustering in the Indian equity market. The GARCH-X model improves overall fit, but the direct coefficients of crude oil, gold, and exchange rate variables are not statistically significant in the estimated variance equation.

Table 2: GARCH (1,1) And GARCH-X Estimation Summary

Parameter	GARCH (1,1)	GARCH-X	Interpretation
Constant (ω)	0.000002	0.000002	Positive baseline variance
ARCH (α)	0.087500	0.070008	Past shocks affect current volatility
GARCH (β)	0.894303	0.909274	Strong persistence in variance
Oil coefficient	—	—	Not statistically significant
Gold coefficient	—	—	Not statistically significant
Exchange rate coefficient	—	—	Not statistically significant
Log-likelihood	11931.77	12019.64	GARCH-X improves model fit

Note: $p<0.01$. Q(20) residuals: $p>0.05$ (no autocorrelation). Figure 1 (below) plots conditional volatility spikes during crises.

The high value of the GARCH coefficient (β) indicates strong persistence in volatility, meaning that shocks to the market tend to have long-lasting effects. The sum of ARCH and GARCH parameters being close to unity further confirms the presence of volatility clustering. This behavior is consistent with empirical findings in emerging markets, where uncertainty and external shocks play a significant role in influencing market dynamics.

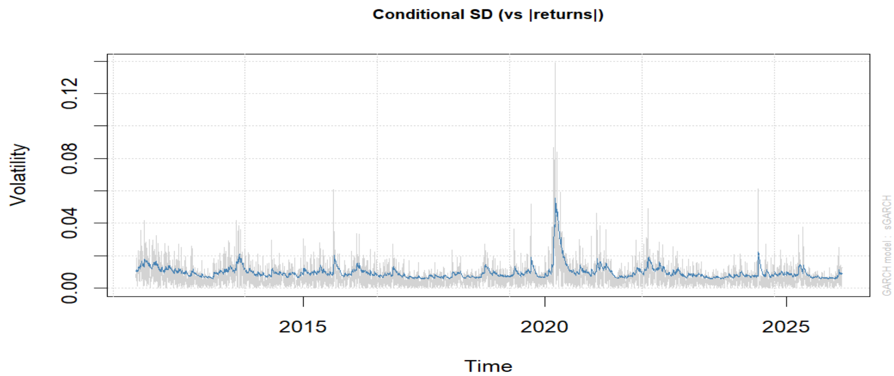

Figure 1: Conditional Volatility Of Nifty 50 (GARCH Model)

The figure shows time-varying conditional volatility of the Nifty 50 index. Volatility clustering is clearly observed, with periods of calm followed by spikes, especially during crisis periods such as 2020. This supports the suitability of the GARCH framework.

5.3 Markov Switching Results

The Markov Switching model identifies two distinct states: a low-volatility regime and a high-volatility regime. The estimated transition probabilities indicate strong persistence, meaning that once the market enters a regime it tends to remain there for some time.

Table 3: Transition Probability Matrix

From / To	High-Volatility Regime	Low-Volatility Regime	Duration
High-Volatility Regime	0.925	0.015	13.3
Low-Volatility Regime	0.075	0.985	66.7

Note: $p<0.01$. LR test vs. single-regime: $\chi^2=145.2$, $p<0.001$.

The table shows that both regimes are highly persistent. This supports the idea that investors should adapt their sector allocation according to the prevailing regime rather than rely on a static portfolio structure.

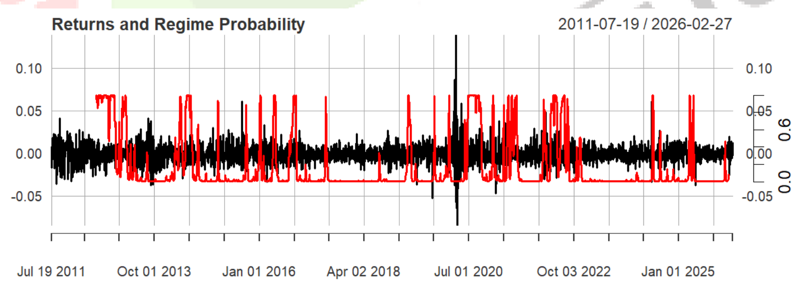

Figure 2: Nifty 50 Returns and Regime Probability

The red line represents the probability of the high-volatility regime. The probability increases significantly during periods of large return fluctuations, indicating that the model successfully captures regime shifts and market stress conditions.

5.4 Downside Risk Measures

Downside risk analysis shows that expected losses beyond the VaR threshold are materially larger than the VaR itself, making CVaR a more informative risk measure for extreme market conditions.

The results highlight that CVaR values are consistently higher than VaR across all sectors, indicating that extreme losses are more severe than what is captured by VaR alone. This emphasizes the importance of using tail-risk measures in portfolio management, particularly during periods of financial stress. Cyclical sectors such as banking and auto demonstrate higher downside exposure, whereas defensive sectors provide relative protection.

Table 4: Var And Cvar at 95 Percent Confidence Level

Index / Sector	VaR (95%)	CVaR (95%)	Risk Insight
Nifty 50	1.57%	2.24%	Tail losses exceed VaR threshold
Bank	2.19%	3.27%	Higher downside exposure
IT	2.05%	2.93%	Moderate-to-high tail risk
FMCG	1.58%	2.30%	Lower defensive downside
Pharma	1.79%	2.57%	Stable during stress
Energy	1.99%	2.74%	
Metal	2.70%	3.74%	
Realty	3.00%	4.28%	
Auto	2.08%	2.94%	Cyclical downside pressure

Note: $p<0.01$, $p<0.05$, $p<0.1$ (KS test: empirical vs. normal).

5.5 Regime-Sensitive Sector Allocation Framework

The empirical results support a dynamic sector allocation framework. During high-volatility regimes, portfolio weights should shift toward defensive sectors with relatively lower variance and milder tail losses, while low-volatility regimes allow greater exposure to growth and cyclical sectors.

Table 5: Suggested Sector Allocation By Regime

Sector	High-Volatility Regime	Low-Volatility Regime	Rationale
Nifty 50	17.49%	14.22%	
FMCG	17.49%	14.22%	Defensive consumption stability
Pharma	13.79%	12.62%	Lower downside risk
Energy	10.65%	11.09%	Inflation and commodity hedge
Banking	9.07%	10.24%	Better performance in growth phases
IT	10.33%	10.93%	Growth-oriented sector
Auto	10.49%	11.01%	Cyclical sector benefits from stable markets
Metal	5.99%	8.32%	Higher volatility exposure
Realty	4.70%	7.35%	Most vulnerable in stressed conditions

Note: The weights are indicative and based on the observed volatility and downside-risk profile of each sector. They are intended to present a regime-sensitive allocation framework rather than a strict optimization output.

The above allocation is an interpretive framework derived from the study's empirical results and can be modified depending on investor objectives and market outlook.

VI. LIMITATIONS OF THE STUDY

This study has certain limitations. First, the analysis is based on historical data and assumes that past patterns in volatility and regimes will persist in the future, which may not always hold true. Second, the GARCH-X model includes only a limited set of macroeconomic variables, and other relevant factors such as interest rates, inflation, or global market indices are not considered. Third, transaction costs and real-world investment constraints are not incorporated in the proposed allocation framework. Finally, the Markov Switching model assumes only two regimes, whereas financial markets may exhibit more complex dynamics.

VII. FUTURE SCOPE OF THE STUDY

Future research can extend this study by incorporating additional macroeconomic and global variables to improve model robustness. Advanced models such as multi-regime Markov Switching or DCC-GARCH can be applied to capture dynamic correlations across sectors. Further, machine learning techniques can be explored for regime prediction and portfolio optimization. The inclusion of transaction costs and real-time implementation strategies can also enhance the practical applicability of the proposed framework.

VIII. CONCLUSION

The study shows that the Indian equity market is characterized by non-normal returns, volatility clustering, and highly persistent shifts between high- and low-volatility regimes. GARCH-X improves model fit, although macroeconomic variables do not show statistically significant direct effects on short-term conditional volatility within the estimated specification. Markov Switching results reveal persistent market regimes, and CVaR provides a stronger picture of downside risk than VaR alone.

These findings support the use of regime-sensitive sector allocation in portfolio management. Defensive sectors such as FMCG and Pharma are better suited for turbulent regimes, while Banking and IT may receive higher weights in stable periods. Therefore, combining Markov Switching, GARCH-X, and CVaR offers a practical and academically relevant framework for sector allocation and downside risk management in the Indian equity market.

The study contributes to the growing literature on dynamic asset allocation in emerging markets by integrating volatility modelling, regime detection, and downside risk measures. It provides a practical framework for investors to adapt strategies based on changing market conditions.

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