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Regime-Aware Portfolio Robustness Across Emerging and Developed Equity Markets

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Abstract

The research investigates how portfolio optimization techniques maintain their effectiveness during different market conditions which affect both emerging and developed equity markets by studying India and Singapore as case studies. The analysis compares mean–variance, minimum variance, equally weighted, and Conditional Value-at-Risk (CVaR) portfolios under both stable and stress market conditions. The research identifies market regimes through a drawdown-based framework which uses an XGBoost classifier that processes macro-financial data including equity index returns and exchange rate movements and implied volatility indicators. The findings show that diversification strategies achieve better results in emerging markets which experience constant market changes while CVaR-based optimization delivers better protection against losses and enhanced results in developed markets with extended stressful periods. The results demonstrate that portfolio strength and optimization success depend on the specific market conditions which affect different regimes.

Keywords: *Portfolio optimization, CVaR, regime detection, emerging markets, developed markets*.

JEL Codes: *G11, G17, G32, C58, C63.*

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Introduction

The mean–variance framework of Markowitz [6] serves as the base for conventional methods of portfolio optimization. The variance-based techniques require two essential conditions which assert that return distributions must remain constant and that both positive and negative risks need identical treatment. The assumptions experience high failure rates because market stress creates situations where static diversification techniques break down due to volatility clustering and correlation breakdowns and extreme tail losses [2, 3].

Conditional Value-at-Risk (CVaR) provides a complete measurement of downside risk which assesses potential extreme losses [9]. The research indicates that CVaR-based optimization delivers better protection against downturns compared to mean-variance methods which fail to safeguard during crisis situations and when returns follow non-normal patterns [12, 1]. The existing research assesses portfolio results by using static market conditions which fail to account for changing market patterns.

The financial markets show regime-dependent behavior because risk structures and correlations and diversification advantages experience changes throughout different time periods which become especially evident during periods of market stress. The research on regime-switching portfolios demonstrates that structural shifts must be considered because their absence results in inconsistent allocation patterns and decreased risk-adjusted outcomes [4, 7]. The current research mainly concentrates on variance-covariance behavior while it almost never applies downside risk optimization to systems that recognize market regimes.

Machine learning has advanced to the point where it can now identify market regimes because it detects nonlinear relationships between macro-financial variables [11, 8]. Data-driven portfolio models that recognize market regimes through machine learning methods are being developed but there remains a lack of empirical proof that connects machine learning with market regime identification.

Data

The research tests portfolio robustness according to different market conditions by analyzing Indian equity data and Singaporean equity data. The two markets provide a clear cross-market comparison because they have different patterns of liquidity and volatility persistence and they operate under distinct regimes.

Asset Universe

Table 1 summarizes the equity universe used for portfolio construction across the two markets.

Table 1: Equity Universe by Market

Market	Constituent Stocks
India (Emerging)	HAL, BEL, TVS Motor, Trent, Varun Beverages, M&M, Tata Power, Coal India, Bharti Airtel, NTPC, IOC, SBI, L&T, Grasim, Sun Pharma
Singapore (Developed)	Keppel, Yangzijiang, Jardine C&C, CapitaLand IC Trust, Singapore Airlines, DBS, Hongkong Land, FCT, OCBC, ST Engineering, SGX, UOB, UOL, Sembcorp, Singtel

Source: Yahoo Finance
Note: Data spans January 2021 to December 2025 with daily adjusted closing prices.

Market Selection

India functions as an emerging market which displays high return variability together with its current market situation and multiple periods of market decline. Singapore functions as a developed market benchmark which exhibits deep liquidity and active institutional trading while maintaining consistent market behavior. The contrast allows evaluation of market-dependent portfolio robustness.

The developed-market representative of Singapore demonstrates its status because its financial system has reached full development and its regulatory system operates effectively and its institutions maintain continuous market operations. The market has strong connections to global capital markets which results in stress periods that connect to worldwide financial disruptions instead of occurring from regional problems. The pattern of stress in emerging markets shows that their markets experience more frequent but specific stress events. The Asian market of Singapore serves as a practical benchmark because it allows researchers to compare two geographically close markets that differ in their trading activity and market development and their base investor types. The presence of dependable high-quality equity data establishes the platform's capability to conduct regime-based portfolio assessment.

Return Construction

The period from January 1, 2021 to December 31, 2025 provides daily adjusted closing prices which researchers use to study all assets. Returns are computed as continuously compounded log returns, uses rolling-window volatility estimates to identify time-varying risk, which the team uses for both regime identification and stress analysis.

Descriptive Statistics

Table 2: Stylized Market Characteristics

	India	**Singapore**
Return dispersion	High, heterogeneous	Low, clustered
Volatility persistence triggering regime shifts	Strong	Weak
Correlation behavior under stress	Sharp tightening	Mild increase
Tail-risk contribution	Asset-specific	Market-wide
Regime structure	Frequent switching	Persistent regimes

Source: Authors' calculations based on Yahoo Finance data
Note: Stylized facts derived from full sample period (2021-2025).

Experimental Design and Methodology

The section presents the empirical design together with its fundamental assumptions and portfolio construction methods and regime identification system and assessment metrics which researchers used to evaluate regime-aware portfolio performance in emerging markets and developed markets equity mar kets. The design enables researchers to assess portfolio performance because it allows them to study how regime shifts affect portfolio development.

Design Assumptions

The experimental framework is built on the following assumptions:

- Markets exhibit time-varying risk characteristics that can be meaningfully partitioned into stable and stress regimes.
- Portfolio weights are held fixed during evaluation to isolate regime effects rather than rebalancing or timing skill.
- All portfolios are long-only and fully invested, reflecting realistic institutional constraints.
- Downside risk is economically more relevant than total variance during stress regimes, particularly in emerging markets.

Portfolio Construction

Table 3 assesses different types of portfolio construction methods through its various benchmark diversification methods and its portfolios that focus on reducing downside risk.

Table 3: Portfolio Construction Methods

Portfolio	Objective and Description
Equally Weighted	Naïve diversification benchmark with equal asset allocation [5].
Minimum Variance	Variance-minimizing portfolio under long-only constraints [6].
Maximum Sharpe (Tangency)	Mean–variance efficient portfolio maximizing the Sharpe ratio [10].
CVaR (Historical)	Minimizes empirical Conditional Value-at-Risk using realized losses [9].
CVaR (Parametric)	CVaR minimization assuming normally distributed returns [12].
CVaR (Monte Carlo)	CVaR minimization using simulated return paths calibrated to empirical moments [1].

Source: Authors' compilation based on cited literature
Note: All portfolios are constructed using daily return data from January 2021.

The process of estimating expected returns and covariance matrices begins with the analysis of historical data. Standard return-risk trade-offs form the basis for mean-variance portfolios, whereas CVaR portfolios focus on achieving minimum tail loss reduction. The analysis maintains constant portfolio weights through its entirety to enable assessment of performance variations across different market conditions.

Backtesting Framework

The evaluation of portfolio performance will be done using the historical daily return data through fixing of portfolio weights to obtain returns. These returns will be used in the analysis of various measures of performance, which include annual return, volatility, Sharpe ratio, Sortino ratio, maximum drawdown, VaR, CVaR, and CAPM alpha.

A rolling window methodology will be used in the estimation of volatility, Sharpe ratio, and CVaR in order to examine the time varying risks and performance of the portfolios. Additionally, CAPM regression will be used to analyze the performance of the portfolios against benchmark returns.

All performance measures will be derived using realized returns without consideration of forward looking information or re-optimization of the portfolio weights.

Stress Regime Identification

The market regimes use a drawdown-based labeling system to determine their current state. The system designates stress periods which occur when portfolio drawdowns exceed an established threshold while it designates all other times as stable. The method establishes actual downside risk through its direct measurement system which does not require hidden market state assumptions.

The Extreme Gradient Boosting (XGBoost) classifier uses macro-financial data including equity index returns and exchange rate movements and implied volatility indices to predict drawdown-based market regimes. The model uses temporal train–test splits to create training data which maintains the actual timing sequence of financial time series data. The classification system uses post-classification smoothing techniques to eliminate short-lived classification noise while stopping sudden transitions between different states. The feature set includes broad market index returns which include NIFTY 50 for India and the STI Index for Singapore and implied volatility indices which include India VIX and VIX and bilateral exchange rate returns. The combined variables measure three different aspects of financial market stress which include overall market direction and investor expectations of future volatility and macroeconomic capital flow dynamics. The regime classification framework excludes portfolio returns as input features for the predictive model. The addition of portfolio returns as explanatory variables would result in look-ahead bias because the regime labels depend on portfolio drawdown data. The classifier uses only market variables which observers can see at the same time to maintain the causal structure of the learning process.

Robustness Evaluation and Ranking

The testing process assesses portfolio robustness by comparing performance metrics that apply to specific market conditions during both regular and crisis periods. The study calculates returns and volatility and Sharpe ratios and drawdowns for each separate market condition.

Researchers employ two distinct ranking systems which enable them to assess performance across multiple markets. The Developing Market Robustness Score (DMRS) measures portfolio strength across the emerging market by giving more importance to performance during harsh market conditions. The developed market uses standardized z-score aggregation to rank portfolios according to their combined risk and return performance across different market conditions. The schemes enable markets to evaluate portfolio strength through their ability to detect changes during different market conditions.

Results

Pre-Stress Portfolio Performance

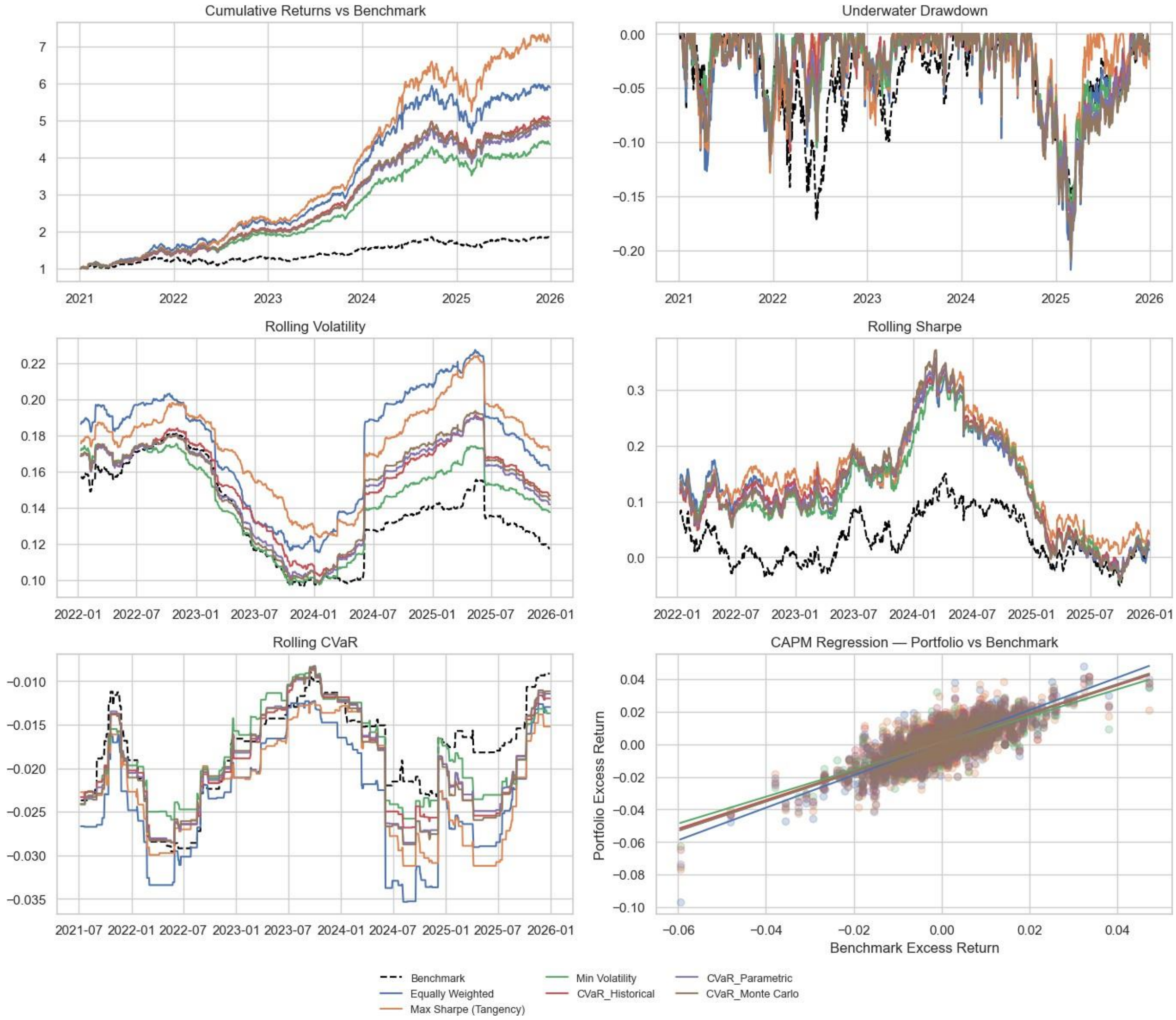
The section tests the basic operational abilities of all investment strategies which were developed before dividing the system into different operational modes. The research investigates how baseline risk–return trade-offs develop through portfolio design which operates under standard market conditions and stable market environments.

Unconditional Performance Dynamics

Figures 1 and 2 compares portfolio performance at two markets The results show cumulative returns and underwater drawdowns and rolling volatility and rolling Sharpe ratios and rolling CVaR and CAPM regression diagnostics.

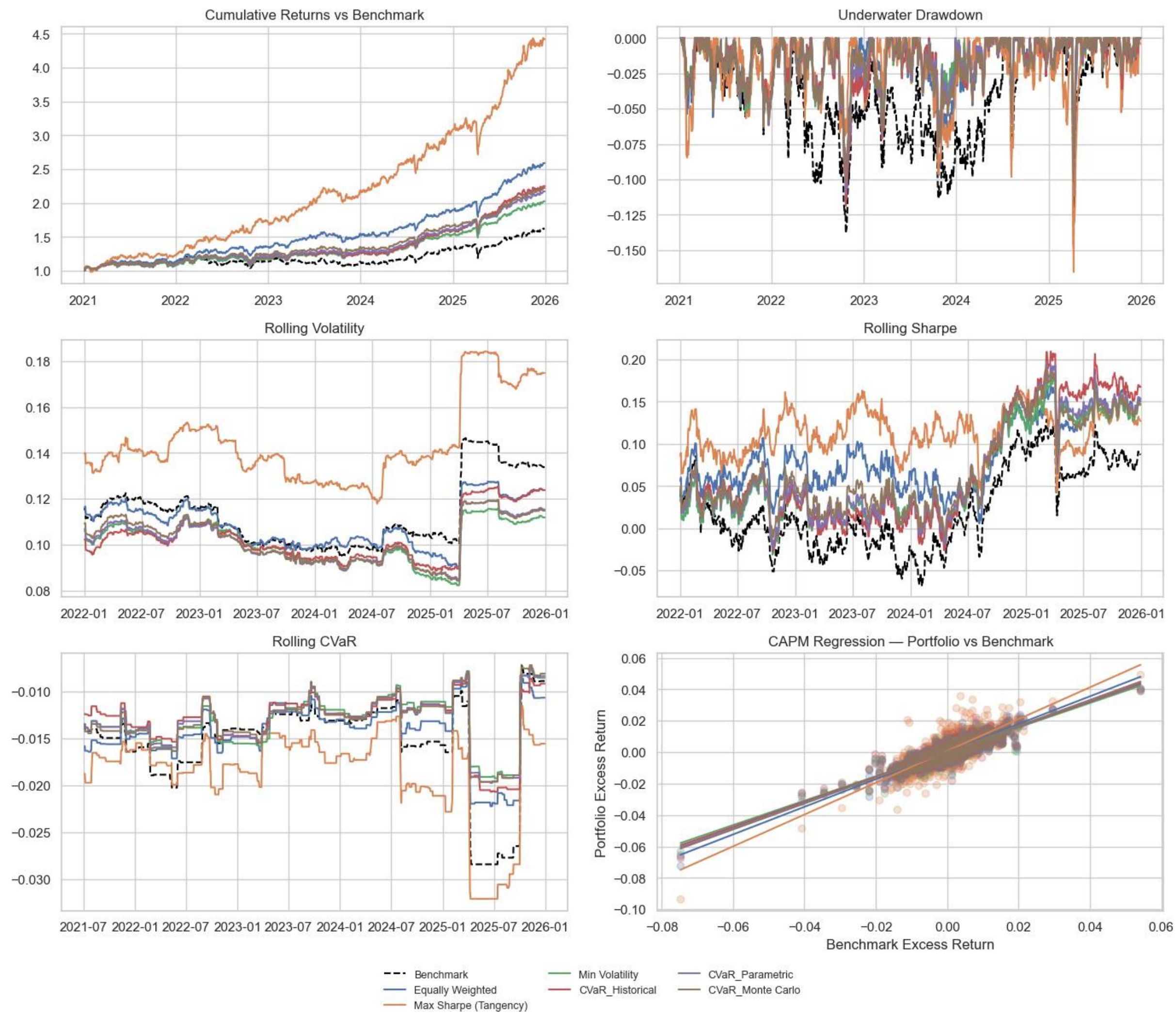
In both markets optimized portfolios deliver better cumulative returns than the benchmark. The Max-Sharpe portfolio achieves the highest return growth but it experiences greater drawdowns. CVaR-based portfolios show smoother drawdown paths because they better control tail risks while minimum-variance portfolios decrease volatility at the cost of return potential.

Figure 1: Unconditional Portfolio Performance Relative to the Benchmark — India



Source: Authors' calculations
Note: Panels show cumulative returns, drawdowns, rolling volatility, rolling Sharpe ratio, rolling CVaR, and CAPM regressions.

Figure 2: Unconditional Portfolio Performance Relative to the Benchmark — Singapore



Source: Authors' calculations
Note: Panels show cumulative returns, drawdowns, rolling volatility, rolling Sharpe ratio, rolling CVaR, and CAPM regressions.

Pre-Stress Performance Summary: India

Table 4: Pre-Stress Performance Summary — India

Portfolio	Return	Volatility	Sharpe	Max DD	CVaR(95%)	Alpha
Equally Weighted	0.437	0.176	2.15	-0.218	-0.025	0.244
Max Sharpe (Tangency)	**0.496**	0.174	**2.51**	-0.205	-0.024	**0.293**
Min Volatility	0.351	**0.148**	1.97	-0.181	-0.020	0.191
CVaR (Historical)	0.391	0.156	2.14	-0.199	-0.022	0.218
CVaR (Parametric)	0.381	0.154	2.09	-0.200	-0.022	0.208
CVaR (Monte Carlo)	0.386	0.155	2.11	-0.210	-0.022	0.212
Benchmark	0.134	0.140	0.54	-0.172	-0.020	0.000

Source: Authors' calculations
Note: All metrics are annualized; Sharpe ratio uses risk-free rate of 0%.

Interpretation. The Max-Sharpe portfolio outperforms all other portfolios in the emerging market because it achieves higher returns and better Sharpe ratio results, but it suffers from bigger drawdowns. The equally weighted portfolio shows competitive performance because it gains advantages from its diversification, while CVaR-based portfolios decrease tail risk yet fail to achieve better returns than other portfolios. The results demonstrate that basic diversification functions as an effective fundamental strategy for emerging markets.

Pre-Stress Performance Summary: Singapore

Table 5: Pre-Stress Performance Summary — Singapore

Portfolio	Return	Volatility	Sharpe	Max DD	CVaR(95%)	Alpha
Equally Weighted	0.211	0.111	1.64	-0.111	-0.015	0.103
Max Sharpe (Tangency)	**0.349**	0.147	**2.17**	-0.165	-0.019	**0.206**
Min Volatility	0.153	**0.102**	1.21	-0.116	-0.014	0.060
CVaR (Historical)	0.177	0.105	1.41	-0.119	-0.014	0.080
CVaR (Parametric)	0.169	0.103	1.35	-0.110	-0.014	0.072
CVaR (Monte Carlo)	0.174	0.103	1.39	**-0.102**	-0.014	0.075
Benchmark	0.104	0.114	0.64	-0.148	-0.016	0.000

Source: Authors' calculations
Note: All metrics are annualized; Sharpe ratio uses risk-free rate of 0%.

Interpretation. Established markets display stronger benefits from optimization than other markets. The Max-Sharpe portfolio delivers better investment results because it generates higher returns and superior Sharpe ratio outcomes while the CVaR Monte Carlo portfolio experiences the smallest loss of value. The market shows less risk-adjusted strategy dispersion than India because of its increased stability.

Key Pre-Stress Insights

Table 6: Key Pre-Stress Insights Across Markets

Dimension	India (Emerging)	Singapore (Developed)
Best pre-stress portfolio	Max-Sharpe, closely followed by Equal-Weight	Max-Sharpe (clear dominance)
Role of diversification	Primary driver of robustness	Secondary to optimization
CVaR effectiveness	Limited return dominance	Strong drawdown control
Drawdown sensitivity	High dispersion across strategies	Low dispersion across strategies
Key implication	Simple strategies remain competitive	Tail-aware optimization is effective

Source: Authors' calculations
Note: Insights derived from pre-stress period analysis.

Implications for Regime-Aware Analysis

The study results show that return-maximizing portfolios achieve better results than pre-stress testing. The study requires evaluation under different market conditions because it shows multiple risks through its drawdown and tail risk results. The following sections examine how portfolio rankings evolve once performance is conditioned on detected stress regimes.

Regime Detection Accuracy

This subsection evaluates the performance of the machine learning-based regime classification framework across emerging and developed equity markets. The system uses drawdown-based stress definitions to define regimes, which the system uses macro-financial variables to make predictions. Our research centers on economic interpretability together with class imbalance effects and cross-market structural differences instead of assessing raw classification metrics.

India (Emerging Market)

Table 7: Regime Detection Performance Summary — India

Portfolio	Accuracy	Stress Recall	Interpretation
Equally Weighted	∼48%	Low (∼15%)	Stress regimes are episodic and weakly aligned with macro signals.
Max Sharpe (Tangency)	∼**62%**	Low (<10%)	Mean–variance portfolios retain macro sensitivity.
Minimum Volatility	∼32%	Very low (<5%)	Volatility smoothing suppresses stress signals.
CVaR (Historical)	∼39%	Very low (<10%)	Downside control dampens drawdown signatures.
CVaR (Parametric)	∼36%	Very low (<10%)	Parametric tail modeling reduces separability.
CVaR (Monte Carlo)	∼28%	Very low (<5%)	Simulated tail protection obscures stress.

Source: Authors' calculations based on XGBoost classification
Note: Accuracy refers to overall classification accuracy; stress recall measures proportion of true stress periods correctly identified.

Key Insight (India): The detection of regimes experiences inherent difficulties because stress events occur with high frequency and specific locations. The portfolio construction method which aims to minimize all downside risks results in diminished performance for the classifier because it fails to identify stress events, which justifies the use of stress-weighted evaluation metrics instead of relying on classification accuracy.

Table 8: Regime Detection Performance Summary — Singapore

Portfolio	Accuracy	Stress Recall	Interpretation
Equally Weighted	∼93%	Low (<5%)	High accuracy driven by dominant stable regimes.
Max Sharpe (Tangency)	∼85%	Moderate	Concentration amplifies sensitivity to global shocks.
Minimum Volatility	∼**97%**	Moderate	Stable variance structure aligns with macro indicators.
CVaR (Historical)	∼98%	Moderate	Tail-risk focus captures rare but systemic stress.
CVaR (Parametric)	∼96%	Moderate	Parametric assumptions fit stable developed markets.
CVaR (Monte Carlo)	∼97%	Moderate	Simulated tail exposure aligns with global risk events.

Source: Authors' calculations based on XGBoost classification
Note: High overall accuracy reflects class imbalance; stress recall remains moderate due to rare event nature.

Singapore (Developed Market)

Key Insight (Singapore): The accurate regime classification system identifies regime states which stay constant until the system encounters difficulties due to extreme class imbalances. Stress regimes exist as infrequent events which operate through global synchronization patterns that require tail-risk–aware portfolios to match macro-driven regime detection methods.

Cross-Market Interpretation

Table 9: Structural Differences in Regime Detectability Across Markets

Dimension	India (Emerging)	Singapore (Developed)
Stress frequency	Frequent, short-lived stress episodes	Rare, persistent stress regimes
Dominant drivers	Domestic equity market movements and exchange rate dynamics	Global volatility indicators and exchange rate movements
Classifier reliability	Economically noisy with blurred regime boundaries	Statistically strong due to regime persistence
Impact of CVaR smoothing	Reduces regime detectability by attenuating drawdown signals	Improves alignment with macro-financial stress indicators
Evaluation implication	Stress-weighted evaluation metrics (DMRS) are required	Composite z-score–based ranking is appropriate

Source: Authors' analysis
Note: Findings based on comparative assessment of regime detection across both markets.

Stress Regime Performance

This section evaluates portfolio behavior during drawdown-defined stress periods by examining how market structure in emerging and developed equity markets affects downside risk.

India (Emerging Market)

Stress regimen shifts in India are dominated by intense perturbations, transient in time, and heterogeneous, accounting for almost 6–12% of the sample period.

Table 10: Stress-Regime Performance Summary — India

Portfolio	Stress Sharpe	Stress MaxDD	Interpretation
Equally Weighted	**3.63**	-6.9%	Diversification dominates stress resilience.
CVaR Monte Carlo	0.98	-7.0%	Balanced downside protection.
Max Sharpe	0.71	-7.1%	Concentration amplifies vulnerability.
CVaR Historical	0.80	-9.1%	Downside smoothing weakens returns.
Min Volatility	0.87	-6.0%	Volatility control limits recovery.
CVaR Parametric	0.05	-12.2%	Parametric tails fail locally.

Source: Authors' calculations
Note: Stress periods constitute approximately 6-12% of the sample period.

Key insight. Diversification rather than complexity optimisation drives stress robustness in the emerging markets.

Singapore (Developed Market)

Stress conditions in Singapore are rare and very persistent, concurring with global risk events.

Table 11: Stress-Regime Performance Summary — Singapore

Portfolio	Z-Score Rank	Stress Sharpe	Interpretation
CVaR Monte Carlo	**1**	5.4	Tail modeling aligns with global stress.
Max Sharpe	2	3.0	Persistent regimes reward concentration.
CVaR Parametric	3	4.9	Parametric assumptions hold.
CVaR Historical	4	3.9	Effective downside protection.
Equally Weighted	5	1.6	Diversification underperforms.
Min Volatility	6	3.7	Variance control insufficient.

Source: Authors' calculations
Note: Stress periods are rare, persistent, and aligned with global risk events.

Key insight. Tail risk optimization trumps diversification in developed markets.

Cross-Market Implications

Table 12: Cross-Market Implications

Dimension	India (Emerging)	Singapore (Developed)
Stress frequency	Frequent, episodic	Rare, persistent
Dominant risk driver	Local drawdowns	Global tail shocks
Best stress portfolio	Equal-weighted	CVaR Monte Carlo
Optimization effectiveness	Limited	Strong
Ranking metric	DMRS	Z-score composite

Source: Authors' analysis
Note: Findings based on stress-period performance evaluation.

Stability Analysis

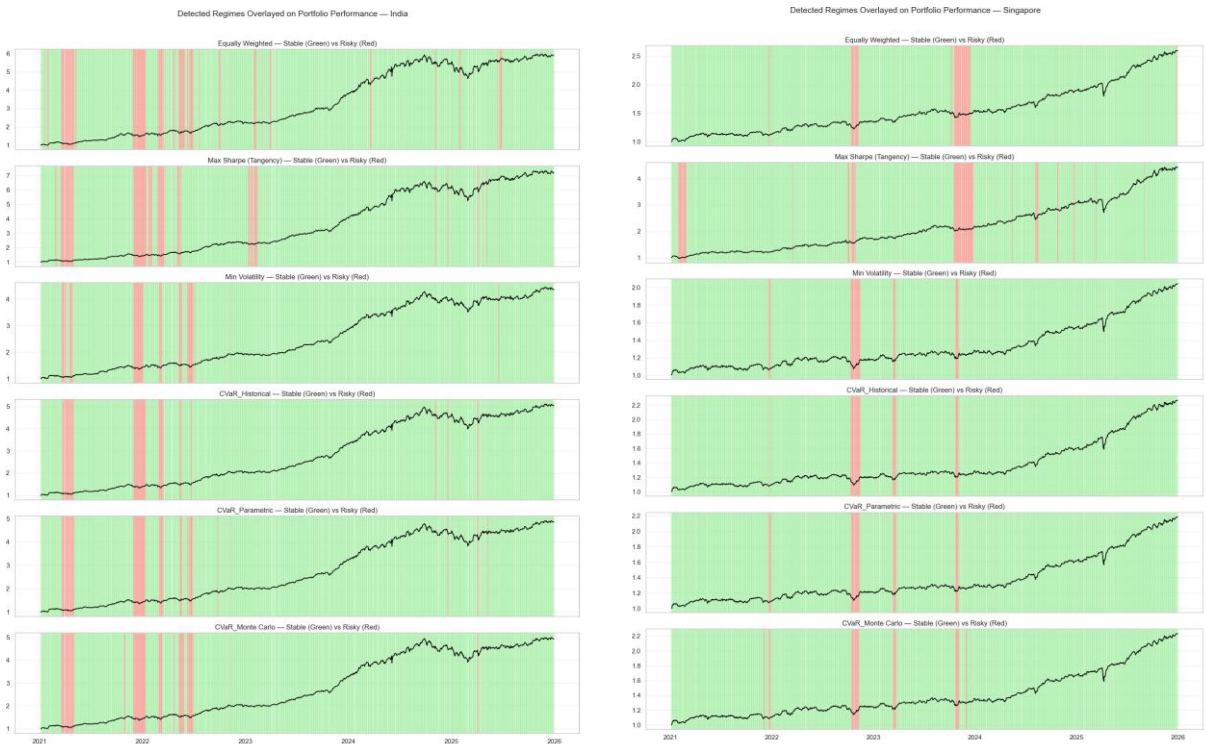
Table 13: Stability Analysis Across Markets

Aspect	India	Singapore
Regime persistence	Low	High
Rolling Sharpe stability	Volatile	Smooth
CVaR stability	Weak	Strong
Diversification benefit	High	Moderate
Design principle	Diversification	Tail-risk optimization

Source: Authors' calculations
Note: Stability metrics computed using rolling windows.

Key Insight. Portfolio stability is market-dependent and governed by regime persistence.

Figure 3: Detected Stress Regimes Overlaid on Cumulative Portfolio Performance



(a) India **(b)** Singapore

Source: Authors' calculations
Note: Shaded regions indicate drawdown-defined stress periods.

Discussion and Conclusion

The research investigates how portfolio resilience varies with different regime conditions in both an emerging market and a developed market through the study of India and Singapore as case examples. The research uses drawdown-based regime labels and machine learning classification methods and CVaR-based portfolio optimization to prove that portfolio strength depends on specific market conditions which do not apply to all market environments.

Market performance depends on two main factors which include how long stress periods last and which specific stress patterns occur in the market. The emerging market faces challenges because it experiences constant short-term stress periods which disrupt optimization systems that depend on stable risk assessments, making tail-risk assessment methods like CVaR less reliable during regime changes. Diversification-based methods, especially equal-weighted portfolios, maintain their strength because they help organizations manage both specific company risks and temporary operational challenges. The developed market contains lengthy periods of stability which break only during rare but intense stress periods that lead to higher predicted downside risk levels. CVaR-based portfolios achieve better protection because they focus on extreme loss events that occur during system-wide crisis periods which explains their better performance in Singapore.

The research results demonstrate that regime-aware portfolio performance depends on three elements: market structure, regime persistence, and the selected risk management approach, which extends beyond the simple calculation of optimization difficulties. Portfolio design should flexibly adjust itself to both regime changes and market dynamics, because different optimization methods fail to deliver effective results across both emerging markets and developed equity markets.

Future Scope

The regime-aware portfolio framework which this study developed requires multiple extensions to achieve further improvements. The study should implement alternative regime identification methods which use hidden Markov models and volatility-switching frameworks to establish their impact on classification stability and economic understanding. The study should examine how cross-asset diversification benefits different asset classes which include bonds and commodities and currencies work under various market conditions.

The upcoming research will investigate how dynamic portfolio rebalancing costs and turnover limitations affect emerging market conditions. The study needs to expand its analysis from emerging markets to developed markets because this would allow better assessment of regime-aware portfolio stability across different worldwide financial markets.

References

[1] Bedoui, R. and Braiek, S. (2023). Cvar-based portfolio optimization under extreme market conditions. Journal of Asset Management, 24:1-18.

[2] Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics, 31(3):307-327.

[3] Cont, R. (2001). Empirical properties of asset returns. Quantitative Finance, 1(2):223-236.

[4] Costa, P. and Kwon, R. (2018). Regime switching and portfolio choice. Journal of Economic Dynamics and Control, 93:179-199.

[5] DeMiguel, V., Garlappi, L., and Uppal, R. (2009). Optimal versus naive diversification: How inefficient is the 1/n portfolio strategy? Review of Financial Studies, 22(5):1915-1953.

[6] Markowitz, H. (1952). Portfolio selection. The Journal of Finance, 7(1):77-91.

[7] Peng, L. and Huang, W. (2022). Regime-dependent asset allocation under downside risk. Finance Research Letters, 46:102327.

[8] Raj, P. and Banerjee, A. (2025). Machine learning based regime-aware portfolio allocation. SSRN Working Paper.

[9] Rockafellar, R. T. and Uryasev, S. (2000). Optimization of conditional value-at-risk. Journal of Risk, 2(3):21-41.

[10] Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. The Journal of Finance, 19(3):425-442.

[11] Sutiene, K. and Maknickiene, N. (2024). Market regime identification using machine learning methods. Expert Systems with Applications, 236:121371.

[12] Trabelsi, A. and Kammoun, S. (2019). Portfolio optimization using conditional value-at-risk. Computational Economics, 54(2):645-672.

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