Research Vidyapith International Multidisciplinary Journal

(International Open Access, Peer-reviewed & Refereed Journal)

(Multidisciplinary, Monthly, Multilanguage)

* Vol-3* *Issue-9* *September 2026*

www.researchvidyapith.com ISSN (Online): 3048-7331

A Comparative Study of Robust Portfolio Optimization under Estimation Errors and Changing Market Conditions in the Indian Stock Market

Dr. Sangita

Assistant Professor, Department of Mathematics, Women's College, Samastipur, LNMU, Darbhanga

Article Info: *(Recieved- 04/07/2026, Accept- 11/08/2026, Published- 05/09/2026)*

DOI- 10.70650/rvimj.2026v3i9005

Abstract

Portfolio weights derived from estimated expected returns and covariance matrices may change substantially when the input observations are revised. This difficulty is especially relevant to equity portfolios experiencing volatility clustering, sectoral shocks and shifting cross-asset relationships. This paper develops a comparative mathematical framework for conventional mean–variance optimization, shrinkage-regularized optimization, ellipsoidal robust mean–variance optimization and conditional value-at-risk (CVaR) optimization in the context of Indian listed equities. It derives the principal optimization formulations, establishes how bounded uncertainty in expected returns introduces a norm penalty, and specifies a rolling out-of-sample evaluation design using National Stock Exchange historical data. An analytical sensitivity discussion and explicitly illustrative figures distinguish theoretical implications from unverified market performance. The comparison indicates that robustness can control unstable allocations and concentration but cannot guarantee higher realized returns, lower drawdowns or superior Sharpe ratios in every regime. Its practical value depends on uncertainty-set calibration, transaction costs, changing correlations and the investor's loss criterion. The paper contributes a reproducible design for evaluating the balance between sampling risk, distributional instability and investment efficiency in Indian equity allocation.

Keywords: robust portfolio optimization; estimation error; mean–variance model; covariance shrinkage; conditional value-at-risk; Indian stock market; uncertainty sets.

1. Introduction

Portfolio optimization converts forecasts about security returns into investment decisions. The apparent precision of an optimal allocation is frequently misleading because expected returns and covariance matrices are themselves estimated from incomplete historical information. A small adjustment to an estimated mean can cause a large reallocation when the corresponding optimization problem is poorly conditioned. In the resulting portfolio, assets may receive extreme weights for reasons that reflect sampling noise rather than durable opportunities.

The problem arises from an asymmetry between statistical estimation and mathematical optimization. A forecasting procedure aims to reduce average estimation error, whereas an optimizer actively identifies the directions in which the estimated inputs seem most favourable. Consequently, the optimizer may magnify apparently

minor inaccuracies. The standard mean–variance formulation of Markowitz (1952) remains foundational, but its practical implementation requires attention to model risk and to the out-of-sample behaviour of the computed weights. Empirical evidence from other markets has demonstrated that complicated estimated allocations do not automatically outperform naive diversification (DeMiguel et al., 2009).

India provides a pertinent context for testing this distinction. The listed equity universe encompasses banking, information technology, energy, consumption, health care, industrial and other sectors whose responses to macroeconomic and international disturbances may differ. Sector exposures and correlations are not fixed over time. During abrupt risk repricing, an apparently diversified portfolio can become more concentrated in common sources of loss. Historical prices and total-return index observations are available through the National Stock Exchange and NSE Indices, allowing a carefully defined empirical test without relying on invented market statistics.

The central question considered here is whether an allocation explicitly designed to account for statistical uncertainty is less sensitive to estimation errors than an allocation treating estimated parameters as exact, and whether that stability comes at an acceptable opportunity cost. The work is comparative and methodological: no claims of measured Indian outperformance are made without an executed backtest. Instead, the paper presents mathematical propositions, evaluation criteria, an implementable research protocol and the limits of the conclusions that may reasonably be drawn.

2. Literature Review

Markowitz (1952) introduced a framework in which portfolio selection depends jointly on expected return and variance. Unlike rules that rank assets only by anticipated yield, mean–variance analysis explicitly incorporates covariance, recognizing that portfolio risk is driven by relationships between asset returns as well as individual volatility. Its familiar quadratic structure permits constrained numerical optimization but assumes usable estimates of the underlying moments.

Black and Litterman (1992) approached unstable implied allocations by combining a market-equilibrium reference with investor views, thereby offering a structured alternative to unconstrained sample-mean estimates. This approach is relevant because much of the instability in conventional optimization can originate in expected-return inputs rather than in covariance estimation alone. However, confidence specifications and equilibrium assumptions introduce additional modelling choices.

Goldfarb and Iyengar (2003) formulated portfolio selection under structured parameter uncertainty and demonstrated how important robust formulations can be handled through tractable conic optimization. Their work supplies the conceptual foundation for representing the unknown mean return as a member of a calibrated uncertainty set instead of treating one point forecast as exact. In the ellipsoidal case, worst-case expected return admits a direct norm-based expression.

Ledoit and Wolf (2004) established the advantages of well-conditioned covariance estimation by combining sample covariance information with a structured target. Shrinkage is especially valuable when the number of assets is not small relative to the number of historical observations. It reduces erratic eigenvalues, improves numerical stability and can protect an optimizer from unstable inversions. Unlike a worst-case uncertainty formulation, however, shrinkage modifies the estimator rather than explicitly minimizing against adverse parameter realizations.

DeMiguel et al. (2009) supplied a particularly demanding benchmark by comparing estimated optimal portfolios with equal weighting. Their out-of-sample analysis warns against treating complex methods as superior merely because they optimize an in-

sample objective. For an Indian-market study, this implies the importance of including 1/N allocation, recording turnover, assessing trading costs and evaluating results across multiple windows rather than drawing conclusions from one favourable segment.

Tail-risk approaches complement the moment-based literature. A variance penalty does not distinguish upside dispersion from negative outcomes, whereas conditional value-at-risk focuses on the average loss in an adverse tail region. This makes CVaR relevant to crash-sensitive investors, although the accuracy of historical tail scenarios remains an open statistical difficulty. The methods reviewed here therefore address different defects: mean–variance captures average quadratic risk, shrinkage stabilizes covariance estimation, robust optimization protects against parameter ambiguity and CVaR targets downside loss.

3. Research Objectives and Hypotheses

The first objective is to compare the mathematical structure and sensitivity of conventional mean–variance, shrinkage-based, ellipsoidal robust and CVaR portfolio designs. The second is to specify a transparent test for the effect of estimation-window length and covariance regularization on realized performance. The third is to examine whether market regimes and trading frictions alter the ranking of methods. The fourth is to identify conditions under which a seemingly conservative optimizer may underperform a simpler benchmark.

The empirical hypotheses to be tested on downloaded market observations are: H1, robust allocation produces lower weight instability than conventional sample mean–variance optimization under otherwise identical constraints; H2, covariance shrinkage reduces portfolio sensitivity when the sample covariance matrix is poorly conditioned; H3, CVaR-oriented portfolios display better realized downside-tail statistics than variance-only portfolios during selected stress windows; and H4, any gross improvement in risk-adjusted returns is attenuated after realistic turnover costs. These are hypotheses, not findings.

4. Mathematical Framework

4.1 Return measurement and sample estimates

Let Pb_{i},t denote the adjusted or total-return-consistent price of security i at observation t and let $rb_{3},t = Pb_{3},t/Pb_{3},t$ " 1. For n assets, collect simple returns in the column vector $w \in \mathbb{R}^{n}$. If there are T observations in the estimation window, the sample mean and unbiased sample covariance are computed as follows:

$$\hat{\mu} = (1/T)\,\Sigma_{t=1}{}^{T} r_t$$

$$\hat{\Sigma} = [1/(T-1)]\,\Sigma_{t=1}{}^{T} (r_t - \hat{\mu})(r_t - \hat{\mu})^{T}$$

Let $w \in \mathbb{R}^{n}$ denote the vector of portfolio weights and $1@_{3}w = 1$ impose full investment. The main analysis uses a long-only feasible set $W = \{w : 1^{T}{}_{3}w = 1, 0$ d" wb_{3} d" ub}; a common cap ub[4] may be used to prevent excessive single-name concentration. Portfolio expected return is $w^{T}\mu$ and portfolio variance is $wT\Sigma w$. Sample estimates are denoted by a hat to distinguish them from unknown population quantities.

4.2 Conventional mean–variance formulation

For risk-aversion coefficient $\gamma > 0$, a penalized mean variance problem maximizes the estimated mean return less the quadratic risk cost:

$$\max \text{ over } w \in W: \; w^{T}\hat{\mu} - (\gamma/2)\, w^{T}\hat{\Sigma} w \quad (1)$$

When $\Sigma\hat{}$ is positive semidefinite, the objective is concave and the feasible constraints are convex. In the unconstrained case, the stationary equation suggests dependence of weights on $\Sigma\hat{}^{-1}\mu\hat{}$, subject to the budget multiplier. This dependence explains why

ill-conditioning and small input perturbations can generate large differences in optimal allocations. Long-only restrictions reduce extreme leverage but do not eliminate concentration or instability.

4.3 Covariance shrinkage and regularization

A stable alternative replaces sample covariance with a combination of sample information and a structured positive-semidefinite target F:

$$\Sigma\tilde{}(\delta) = (1 - \delta)\Sigma\hat{} + \delta F, \quad 0 \le \delta \le 1 \quad (2)$$

The shrinkage intensity ä governs the trade-off between responsiveness to observations and stability. An appropriately estimated data-dependent intensity is preferable to arbitrary tuning selected on the test period. Typical targets include scaled identity or constant-correlation structures. In the comparison below, the shrinkage portfolio solves Equation (1) with $\Sigma\tilde{}$ in place of $\Sigma\tilde{}$, while using the same feasible set and common forecast convention.

A closely related allocation constraint penalizes concentrated weights by including $-\eta\|w\|_2^2/2$ in the objective. This ridge-type regularization can suppress abrupt changes in allocation, though it does not itself model adverse variation in expected returns. Shrinkage and weight regularization should be reported separately because their statistical meanings differ.

4.4 Ellipsoidal uncertainty in expected returns

Suppose estimated means are imperfect and the unknown mean vector belongs to an ellipsoid centred at $\mu\hat{}$, Define the uncertainty set $U\mu = \{\mu\hat{} + Au : \|u\|_2 \le \rho\}$, where A controls the shape and scale of perturbations and, $\rho \ge 0$ sets their radius. The investor chooses weights against the least favourable admissible mean:

$$\max \text{ over } w \in W : \min \text{ over } \mu \in U\mu \ [w^T\mu - (\gamma/2)\, w^T\Sigma\tilde{}w \quad (3)$$

Because $\min_{\{\|u\|_2 \le \rho\}} w^T Au = -\rho\, A^T wA2$ by Cauchy–Schwarz duality, Equation (3) is exactly equivalent to:

$$\max \text{ over } w \in W : wT\mu\hat{} - \rho\|ATw\|_2 - (\gamma/2)wT\Sigma\tilde{}w \quad (4)$$

The additional norm term is a penalty for exposure to uncertain directions. If A is diagonal with larger elements for assets whose estimated returns are less reliable, the model discourages allocating heavily to those fragile forecasts. Equation (4) is a concave maximization over a convex set provided ÓÞ is positive semidefinite; it can also be written as a second-order cone program with an auxiliary variable z and constraint . The parameter ñ must be chosen using training information, confidence-set calibration or nested validation rather than the eventual test returns.

4.5 Covariance uncertainty and tractability

Mean ambiguity is not the only source of instability. Correlations and variances may change, especially during extreme market movements. A generic formulation permits covariance Σ to vary over a positive-semidefinite set $U\Sigma$ and evaluates the largest admissible quadratic risk:

$$\max \text{ over } w\ T\ W : \min \text{ over } \mu\ U\mu,\ \Sigma U\Sigma \left[wT\mu - (\gamma/2)wT\Sigma w\right] \quad (5)$$

The computational burden depends on the geometry of $U\Sigma$ A useful illustrative bound is $U\Sigma = \{\Sigma\tilde{} + \Delta : \Delta$ Ä symmetric, $\|\Delta\|F \le \varepsilon,\ \Sigma\tilde{} + \Delta\ 0\}$. With the positive-semidefinite feasible perturbation $\Delta = \varepsilon wwT/\|w\|_2^2$ for nonzero w, and by matrix norm duality, the worst-case quadratic risk is $wT\Sigma\tilde{}w + \varepsilon\|w\|_2^2$. Thus the covariance-robust penalty acts like an additional concentration or ridge penalty when uncertainty is measured by a Frobenius-norm ball. A choice of uncertainty set therefore determines not only robustness but also the resulting economic bias.

4.6 Conditional value-at-risk optimization

Define the portfolio loss in scenario t as $\mathrm{LT}(\mathrm{w}) = -\mathrm{wTrT}$. For confidence level $\alpha \in (0,1)$, sample CVaR may be optimized through a threshold variable ξ and nonnegative excess-loss variables ξt. The empirical minimization problem is:

$$\textit{min over } w,\ \zeta,\ \xi:\ \zeta + \left[1/\left((1-\alpha)T\right)\right] \Sigma t\ \xi t \quad (6)$$

$$\textit{subject to } \xi t \geq -wTrt - \zeta, \xi t \geq 0, w \in W$$

Equation (6) is a linear program when the portfolio loss is linear and the only allocation conditions are linear. The confidence level, for example $\alpha = 0.95$, must be declared before evaluation. CVaR is designed to measure the mean of adverse tail losses under the empirical scenario distribution; it is not automatically distributionally robust. Historical samples can omit future crashes, so stress scenarios and rolling validation remain important.

5. Indian Market Data and Empirical Research Design

5.1 Sample construction

The proposed investable universe is the constituent set of a broad, liquid NSE index, with NIFTY 50 serving as a practical initial choice. To avoid survivorship bias, index membership should be reconstructed as it existed on each portfolio formation date, using contemporaneous constituent records when obtainable. Stocks with unavailable valid observations require a stated missing-data rule; a retrospectively selected set of today's survivors must not be presented as an unbiased historical universe. If point-in-time constituents are unavailable, the scope of inference should be explicitly narrowed to a fixed-constituent illustration.

Daily adjusted closing prices and corporate action adjustments are preferable to unadjusted price series. Where an investable total-return equivalent is available, distributions should be accounted for to ensure fair comparison. NSE Indices publishes historical data resources and total-return index values; these are suitable sources for benchmark construction. A sample such as January 2015 through December 2025 could offer multiple regimes, but the start and end dates must be defined against the actual downloaded coverage, and no observation through 2026 is assumed in the numerical analysis here.

5.2 Rolling training and testing

A rigorous comparison uses a rolling-origin design. For each formation date, estimate means and covariance matrices over a trailing window of 252, 504 or 756 trading days. Fit any shrinkage intensity and robustness radius using only that training interval or an inner training–validation split. Compute model weights, hold them for the next 21 trading days or an equivalent monthly schedule, record realized daily portfolio returns, and repeat without allowing test-period information to enter estimation.

Monthly rebalancing balances responsiveness with implementability; additional quarterly rebalancing can test turnover sensitivity. The equal-weight reference must follow the same calendar and asset-eligibility rules. The methods should be compared with identical upper weight bounds, sector constraints if used, expected-return estimator, universe and transaction-cost assumptions wherever applicable. Otherwise improvements attributed to robust optimization might merely reflect unequal constraints.

5.3 Market-regime classification

Changing market conditions should be defined with observable rules rather than

impressionistic labels. One method computes a trailing 60-day annualized index volatility using only information known at the formation date. A high-volatility state may be assigned when this measure exceeds a predetermined training-sample percentile; remaining observations form the normal-volatility state. A second classification can identify substantial index drawdowns or increasing average asset correlations, again avoiding look-ahead bias.

It is important to separate regime definitions from regimes used to tune the model. A model calibrated after observing a severe episode can exaggerate predictive ability. Sensitivity analysis should vary the volatility threshold, training length and portfolio cap and should document whether results remain qualitatively similar. Sub-period findings should report the number of observations and confidence intervals, particularly when stress intervals are short.

5.4 Comparison metrics

The primary measures are annualized arithmetic mean return, annualized realized standard deviation, Sharpe ratio using a specified contemporaneous risk-free proxy, maximum drawdown, historical 95% CVaR of daily losses, average turnover and effective number of holdings. Effective diversification can be represented by $N_eff = 1/\Sigma i wi^2$. Weight instability is assessed through average absolute allocation changes and sensitivity to perturbed training inputs. Parameter instability is also quantified by condition number $\kappa(\Sigma^)$, where a large value indicates that small numerical disturbances may be magnified by inversion.

Inference requires care because strategy returns share assets and overlap calendar intervals. Paired differences in realized daily returns, block-bootstrap confidence intervals for Sharpe and drawdown statistics, and reporting the number of rebalance decisions can be more informative than unadjusted independent-sample t-tests. Model selection across many settings introduces multiple-testing risk. The preferred configuration should therefore be fixed in training and evaluated on a reserved test period.

6. Comparative Analysis and Analytical Results

Without an executed Indian stock-data backtest, the defensible results are mathematical rather than empirical. The robust objective in Equation (4) is never larger, at the same candidate weights, than the nominal objective when ñ > 0. This does not imply that its realized return will be smaller or larger. Instead, it establishes the price paid within the optimization criterion for protection against departures from estimated means. Likewise, shrinkage alters the spectrum of the covariance estimate and may reduce numerical instability, but it need not be closer to the future covariance in every sample.

Consider a two-security example with estimated weekly expected returns $\mu^ = (0.003, 0.002)$ and uncertainty scales $A = \mathrm{diag}(0.002, 0.0005)$. If $\gamma = 0$ and shorting is disallowed, the nominal objective favours the first security. A robust investor with $\rho = 1$ assigns a larger uncertainty charge to heavy exposure in the first security. The exact optimal mixture depends on the norm interaction between exposures; it cannot be inferred by separately subtracting one standard error from each asset and ranking the results. This difference illustrates the geometry of joint uncertainty and the role of diversification within the ambiguity penalty.

Sensitivity also follows from first-order conditions. In an unconstrained quadratic problem with nonsingular covariance, perturbing the expected-return vector by äì induces, holding the covariance fixed, a weight response proportional to $\Sigma^{-1}\delta\mu/\gamma$ up to the full-investment projection. The operator norm of this response can become large

as the smallest eigenvalue of Ó approaches zero. Increasing the smallest eigenvalue through covariance regularization reduces this mechanism, though its realized investment benefit remains sample dependent.

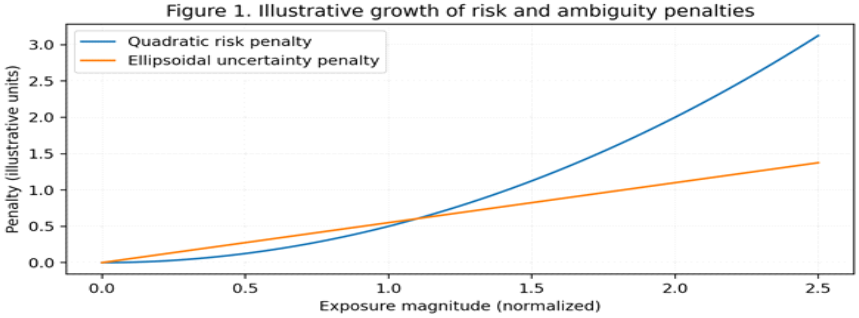
6.1 Model comparison

Approach	Main uncertainty treatment	Principal advantage	Principal limitation
Mean–variance	Point estimates of μ and Σ	Transparent convex benchmark	High sensitivity to sample inputs
Covariance shrinkage	Regularizes Ŝ toward F	Improves conditioning	Target/intensity can be misspecified
Ellipsoidal robust	Worst-case mean within Uμ	Explicit ambiguity protection	May sacrifice upside; radius calibration
CVaR	Historical adverse loss scenarios	Direct downside-loss focus	Tail scenarios may be sparse
Equal-weight 1/N	No sample-moment optimization	Low model complexity	Ignores estimated opportunities and risk heterogeneity

The relative strengths of these approaches depend on which source of uncertainty dominates. If expected-return estimation is exceptionally noisy, the norm penalty in robust optimization may meaningfully restrict concentrated forecasts. If covariance instability is the main concern, shrinkage can provide a simpler intervention. When extreme negative returns are the dominant investment objective, CVaR may be appropriate. No mathematical theorem establishes a single universally superior optimizer across all market distributions, loss functions and cost structures.

6.2 Illustrative graphs

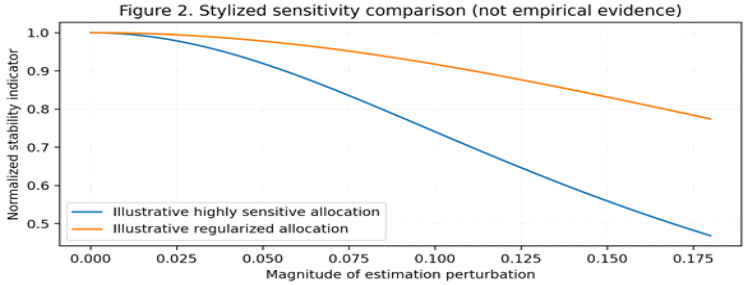
Figure 1. Illustrative growth of risk and ambiguity penalties



Note. Figure 1 plots conceptual functions on normalized axes. The curves are not estimated from Indian stock-market observations.

Figure 1 emphasizes that the quadratic variance penalty and the norm-based ambiguity penalty grow differently with exposure. Their relative importance changes as ã, ñ and the shapes of the covariance matrix and uncertainty set change. A numerical optimizer therefore trades off compensation for return, covariance exposure and vulnerability to mean-estimation errors.

Figure 2. Stylized sensitivity comparison (not empirical evidence)



Note. Figure 2 presents illustrative functional shapes only; the vertical axis is a hypothetical stability indicator, not a measured portfolio statistic.

Figure 2 visualizes the interpretation of a regularized allocation as less responsive to small estimation disturbances. The graph is not evidence that any particular Indian portfolio achieved these values. A genuine empirical sensitivity plot should repeatedly

perturb the training samples, recompute actual weights and present median weight displacement or dispersion across trials.

6.3 Reporting template for actual backtest

Statistic	Mean–variance	Shrinkage	Robust	CVaR	1/N
Annualized net return	To calculate	To calculate	To calculate	To calculate	To calculate
Annualized volatility	To calculate	To calculate	To calculate	To calculate	To calculate
Sharpe ratio	To calculate	To calculate	To calculate	To calculate	To calculate
Maximum drawdown	To calculate	To calculate	To calculate	To calculate	To calculate
95% loss CVaR	To calculate	To calculate	To calculate	To calculate	To calculate
Average turnover	To calculate	To calculate	To calculate	To calculate	To calculate

Entries deliberately remain unfilled until historical observations have been downloaded, cleaned and processed. Replacing them with fabricated percentage returns would make the study irreproducible. In a completed empirical report, the table should be supplemented by the exact sample dates, asset count, rebalance schedule, cost assumption, risk-free series and confidence intervals for paired performance differences.

7. Discussion

The underlying distinction between optimality and robustness is one of the most important conclusions of the mathematical comparison. Nominal optimality is conditional on assumed parameters; robust optimality addresses a specified neighbourhood of alternatives. The latter does not correct every conceivable error. If the true mean lies far outside the ellipsoid, a portfolio can remain highly exposed to adverse outcomes. Conversely, a very large radius may force overly cautious weights and give up genuine excess return.

Calibration of the uncertainty set is therefore an economic and statistical decision. Treating ñ as an unexplained tuning constant makes the model difficult to interpret. A defensible procedure may estimate forecast-error covariance across nested rolling windows and use a prespecified confidence radius, carefully accounting for serial dependence and the fact that return means are often hard to estimate. Alternatives include bootstrapping training periods or using a scenario set informed by stress episodes, provided future returns do not leak into the calibration process.

The Indian equity context places additional importance on feasible trading. Rebalanced securities may face unequal trading costs and liquidity. Stocks enter and leave indices, sector composition changes, and risk measures are sensitive to corporate-action handling. A large-sample backtest built from the final surviving constituent list would risk overstating historical implementability. These data decisions may influence observed method rankings as much as the choice between a quadratic program and a conic program.

An investor should not equate low realized volatility with protection from a severe drawdown. Correlations can rise when diversification is most valuable. The covariance matrix may be stable over many quiet observations yet describe a radically different state during market-wide selling. Combining moderate covariance shrinkage with explicit mean uncertainty and stress-aware loss constraints may be more defensible than selecting one technique to solve all problems. Nevertheless, adding layers of optimization increases model-selection degrees of freedom; each additional parameter requires validation.

There is also a difference between statistical and economic significance. A small improvement in gross Sharpe ratio could disappear after turnover costs and uncertainty in the estimate of the Sharpe ratio itself. The reported comparison should therefore

prioritize net performance, allocation stability and out-of-sample reproducibility instead of selecting the strategy with the largest backtested return. Publication-quality analysis should disclose unprofitable regimes and unsuccessful specifications, rather than only the best-performing combination.

8. Limitations and Directions for Further Research

This article is a comparative mathematical study with a proposed empirical protocol; it does not contain a completed backtest on Indian securities. Accordingly, it cannot establish the numerical magnitude or statistical significance of robustness benefits in India. The two figures are theoretical illustrations and cannot be cited as observations. The absence of a fully reconstructed point-in-time security universe and complete trading-cost records is an additional limitation for any later implementation.

The framework assumes that historical first and second moments and an uncertainty geometry provide useful approximations to future asset behaviour. Changes in liquidity, regulation, corporate structure, taxation and market participation can violate those approximations. The CVaR formulation relies on an empirical tail whose precision is limited by the number and variety of scenarios. Regime classifications based only on trailing realized volatility may also fail to detect sudden structural breaks before they occur.

Further studies could compare ellipsoidal and distributionally robust ambiguity sets, use factor-based covariance estimators, incorporate transaction-cost-aware optimization directly into the objective, and test allocations on small-cap versus large-cap universes. A particularly useful extension would distinguish forecast uncertainty from regime uncertainty by allowing different covariance and expected-return specifications conditional on information available at each rebalance date. Such refinements should be judged by out-of-sample stability and investor welfare, not complexity alone.

9. Conclusion

Robust portfolio selection provides a mathematically coherent response to the fact that historical estimates are uncertain. Under ellipsoidal mean uncertainty, the worst-case formulation becomes a standard mean–variance objective with an additional norm penalty. Covariance shrinkage improves conditioning by trading some responsiveness for stability, while CVaR offers a different representation of undesirable tail outcomes. These strategies differ in the uncertainty they address and should not be regarded as interchangeable.

For the Indian stock market, the decisive empirical question is not whether a method is optimal under its assumptions but whether its allocations remain useful after realistic estimation errors, regime changes and trading costs. The proposed rolling design provides a foundation for answering that question transparently. Until such a backtest is performed, superiority over traditional optimization or equal weighting remains an open hypothesis. The broader implication is that credible portfolio research must test robustness of decisions as carefully as it estimates expected investment performance.

Author's Declaration:

I/We, the author(s)/co-author(s), declare that the entire content, views, analysis, and conclusions of this article are solely my/our own. I/We take full responsibility, individually and collectively, for any errors, omissions, ethical misconduct, copyright violations, plagiarism, defamation, misrepresentation, or any legal consequences arising now or in the future. The publisher, editors, and reviewers shall not be held responsible or liable in any way for any legal, ethical, financial, or reputational claims related to this article. All responsibility rests solely with the author(s)/co-author(s), jointly and severally. I/We further affirm that there is

no conflict of interest financial, personal, academic, or professional regarding the subject, findings, or publication of this article.

References

1. Black, F., & Litterman, R. (1992). Global portfolio optimization. Financial Analysts Journal, 48(5), 28–43. https://doi.org/10.2469/faj.v48.n5.28
2. DeMiguel, V., Garlappi, L., & Uppal, R. (2009). Optimal versus naive diversification: How inefficient is the 1/N portfolio strategy? The Review of Financial Studies, 22(5), 1915–1953. https://doi.org/10.1093/rfs/hhm075
3. Goldfarb, D., & Iyengar, G. (2003). Robust portfolio selection problems. Mathematics of Operations Research, 28(1), 1–38. https://doi.org/10.1287/moor.28.1.1.14260
4. Ledoit, O., & Wolf, M. (2004). A well-conditioned estimator for large-dimensional covariance matrices. Journal of Multivariate Analysis, 88(2), 365–411. https://doi.org/10.1016/S0047-259X(03)00096-4
5. Markowitz, H. (1952). Portfolio selection. The Journal of Finance, 7(1), 77–91. https://doi.org/10.1111/j.1540-6261.1952.tb01525.x
6. NSE Indices Limited. (n.d.). Historical data reports. https://www.niftyindices.com/reports/historical-data
7. National Stock Exchange of India. (n.d.). All reports: Historical index data. https://www.nseindia.in/all-reports.

Cite this Article

'Dr. Sangita', "A Comparative Study of Robust Portfolio Optimization under Estimation Errors and Changing Market Conditions in the Indian Stock Market", Research Vidyapith International Multidisciplinary Journal, ISSN: 3048-7331 (Online), Volume:3, Issue:9, September 2026.

"Copyright © 2026 The Author(s). This work is licensed under Creative Commons Attribution 4.0 (CC-BY), allowing others to use, share, modify, and distribute it with proper credit to the author."