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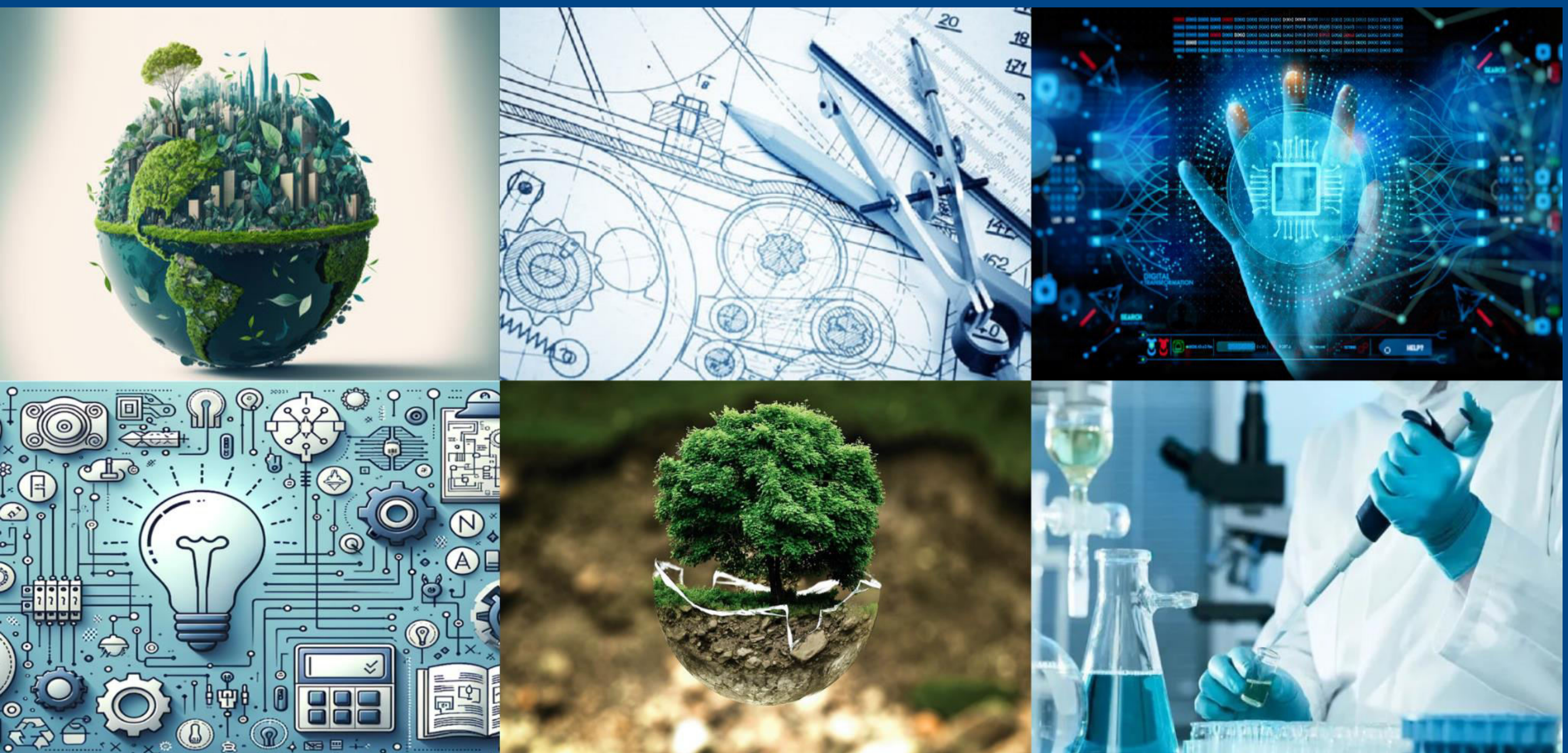

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A study on Optimal Portfolio Selection using Sharpe Ratio Analysis of Nifty 50 Stocks

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ABSTRACT: This study investigates the construction of an optimal investment portfolio from Nifty 50 constituent stocks using the Sharpe Ratio as the primary screening and optimization criterion, covering January 2021 to December 2025. Employing Python-based data analysis including historical return computation, annualized volatility estimation, trend analysis, and Monte Carlo portfolio simulation (5,000 iterations), the research identifies a five-stock optimal portfolio comprising SHRIRAMFIN.NS, HINDALCO.NS, BPCL.NS, EICHERMOT.NS, and HEROMOTOCO.NS. Markowitz Mean-Variance optimization assigns weights of 20.00%, 31.95%, 16.51%, 1.70%, and 29.84% respectively, yielding an annualized return of 44.93%, portfolio volatility of 12.92%, and a Maximum Sharpe Ratio of approximately 3.4, more than seven times the Nifty 50 benchmark Sharpe Ratio of 0.4688. Statistical hypothesis testing confirms a strong positive risk-return relationship (Pearson r = 0.8144, p = 0.047, R-squared = 0.663), consistent with Modern Portfolio Theory and CAPM. Sector analysis reveals that automobile and basic materials stocks deliver the strongest risk-adjusted returns, while IT and FMCG underperform. The methodology is robust to risk-free rate variation (5.0%-7.5%) and modest annual rebalancing costs (0.10%-0.30%), making it accessible to both retail and institutional investors in the Indian equity market.

KEYWORDS: Nifty 50, Portfolio Optimization, Sharpe Ratio, Risk-Return Analysis, Markowitz MPT, CAPM, Indian Equity Market

I. INTRODUCTION

The Nifty 50 index -- comprising 50 of India's largest and most liquid companies listed on the National Stock Exchange (NSE) -- accounts for approximately 65% of NSE's free-float market capitalization and serves as the primary benchmark for India's equity market. As India continues to emerge as one of the world's fastest-growing large economies, effective portfolio management within the Nifty 50 universe demands a disciplined, risk-adjusted framework.

The Sharpe Ratio, introduced by Nobel laureate William F. Sharpe (1966), measures excess return per unit of total risk, enabling investors to compare portfolios on a risk-adjusted basis. While portfolios constructed through Sharpe Ratio maximization have demonstrated superiority over equally weighted and market-cap-weighted alternatives in several international markets, empirical evidence specific to the Indian equity market remains limited. This study addresses that gap by applying Python-based quantitative analysis and Markowitz Mean-Variance Optimization to construct and validate a Sharpe Ratio-optimized portfolio from Nifty 50 stocks over the 2021-2025 period -- a span covering post-COVID recovery, inflationary shocks, monetary tightening, and domestic growth cycles that collectively test portfolio methodologies across diverse market regimes.

II. LITERATURE REVIEW

Markowitz (1952) established the theoretical foundation of Modern Portfolio Theory (MPT), demonstrating that mean-variance optimization produces an efficient frontier of portfolios offering the maximum return for a given risk level. Sharpe (1966) subsequently introduced the Sharpe Ratio as a standardized measure of risk-adjusted performance, enabling cross-portfolio comparisons that account for both return and volatility.

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Empirical research on Indian equity markets confirms that the Nifty 50 exhibits characteristics of weak-form efficiency (Mittal & Jain, 2009), suggesting that quantitative screening can generate consistent risk-adjusted excess returns. Sen et al. (2021) demonstrated that hierarchical risk parity and minimum variance strategies applied to Nifty 50 stocks outperform passive index exposure, while Narayan and Reddy (2018) confirmed that optimal diversification within the index requires a smaller stock subset during stable markets. Fathali et al. (2022) and Idrees et al. (2019) further document that statistical and quantitative approaches to portfolio construction outperform heuristic methods in Indian market contexts.

Sector-level studies reveal heterogeneous risk-return dynamics across Nifty 50 constituents. Financial services, consumer durables, and basic materials stocks exhibit superior Sharpe Ratios compared to IT, FMCG, and utilities during domestic growth cycles, while defensive sectors demonstrate relative outperformance during monetary tightening phases. Malhotra and Bagrecha (2024) confirm that macroeconomic factors -- particularly global liquidity and domestic monetary policy -- exert asymmetric effects on Nifty 50 performance, underscoring the importance of sector-aware portfolio construction. Despite this body of work, no study has systematically applied Python-based Sharpe Ratio screening and Markowitz optimization to construct and validate a concentrated Nifty 50 portfolio across the full 2021-2025 market cycle.

III. RESEARCH OBJECTIVE AND HYPOTHESES

This study pursues four core research objectives:

- Analyse the risk-return characteristics of all Nifty 50 constituent stocks over 2021-2025.
- Construct an optimal portfolio by selecting and weighting stocks based on Sharpe Ratio maximization.
- Evaluate the statistical significance of the portfolio's risk-adjusted performance relative to the Nifty 50 benchmark.
- Assess the robustness and practical implementability of the Sharpe Ratio optimization framework.

Table 1: Research Hypotheses and Statistical Tests

Hypothesis	Test Applied	Outcome
H1: Significant positive risk-return relationship exists across Nifty 50 stocks (MPT/CAPM)	Pearson correlation + linear regression	r = 0.8144, p = 0.047 → Supported
H2: Sharpe Ratio portfolio achieves higher risk-adjusted return than equal-weight portfolio	SR comparison (MSR vs. equal-weight)	SR 3.4 vs. lower EW SR → Supported
H3: Portfolio annualized return significantly exceeds risk-free rate; volatility lower than avg. individual stocks	One-sample t-test	44.93% vs. 6.5% RF; 12.92% vs. 27.70% avg vol → Supported
H4: Optimized portfolio Sharpe Ratio significantly exceeds Nifty 50 benchmark SR	Independent two-sample t-test	SR 3.4 vs. 0.4688 benchmark → Supported

IV. RESEARCH METHODOLOGY

4.1 Data and Sample

The study uses daily closing price data for all 49-51 Nifty 50 constituent stocks from January 2021 to December 2025, sourced via the yfinance Python library (Yahoo Finance), cross-validated with MoneyControl and NSE India. Two datasets are constructed: (i) a 5-year daily dataset (1,236 observations) for long-term return, volatility, and trend analysis; and (ii) a monthly end-of-period 2025 dataset for portfolio optimization. The Nifty 50 index itself serves as

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the benchmark, with an approximate Sharpe Ratio of 0.4688 and ~14% CAGR over the study period. The risk-free rate is set at 6.5%, reflecting the RBI repo rate prevailing during 2021-2025.

4.2 Analytical Framework

The methodology follows a sequential quantitative framework. Annualized returns are computed as the compound percentage change in closing prices over the 5-year window. Annualized volatility is calculated as the standard deviation of daily log returns scaled by sqrt252, consistent with standard financial practice. The Sharpe Ratio for each stock is computed as (annualized return − risk-free rate) ÷ annualized volatility. Log returns are used for portfolio-level calculations to ensure lognormal compounding consistency:

$\text{Returns} = \ln(P_t / P_{t-1})$ | $\text{Annual Return} = \text{mean(Returns)} \times 12 \times 100$ | $\text{Annual Risk} = \text{std(Returns)} \times \text{sqrt}12 \times 100$

Trend analysis employs 50-day and 200-day simple moving averages to identify Golden Cross (bullish) and Death Cross (bearish) signals for representative stocks (TCS, Reliance). Monthly seasonality analysis identifies systematic return patterns for ICICIBANK across calendar months. Portfolio optimization employs Markowitz Mean-Variance Optimization via Monte Carlo simulation of 5,000 randomly weighted portfolios (weights normalized to sum to 1), from which the Maximum Sharpe Ratio portfolio is extracted.

V. DATA ANALYSIS AND RESULTS

5.1 Preliminary Analysis: Return and Volatility Dispersion

The cross-sectional analysis of all 49 Nifty 50 stocks reveals extreme heterogeneity in both return and risk over 2021-2025. Cumulative 5-year returns range from BEL.NS at +930.82% to INDUSINDBK.NS at −4.83%, with the top five gainers (BEL, Coal India, NTPC, M&M, ONGC) all exceeding 277% returns -- driven respectively by defense sector capex, energy demand, infrastructure expansion, EV strategy, and crude oil recovery. The top five losers (INDUSINDBK, HDFCLIFE, TCS, Asian Paints, HUL) reflect sector-specific headwinds: governance concerns, insurance valuation compression, global IT spending slowdown, paint input cost pressures, and FMCG volume deceleration.Annualized 5-year volatility confirms significant sectoral patterning. The most volatile stocks -- ADANIENT.NS (49.75%), ADANIPORTS.NS (38.22%), SHRIRAMFIN.NS (34.89%) -- are concentrated in the Adani conglomerate and NBFC sectors, where event-driven and credit risk amplify price swings. Defensive stocks NESTLEIND.NS (18.68%), ITC.NS (20.10%), and HINDUNILVR.NS (20.13%) exhibit the lowest annualized volatility, consistent with their stable, non-cyclical earnings streams. Average cross-sectional correlation of approximately 0.60-0.65 among Nifty 50 stocks confirms that meaningful diversification benefits are achievable within the index.

Table 2: Annual Return and Risk -- Selected Nifty 50 Stocks (2025 Monthly Data)

Stock	Annual Return (%)	Annual Risk (%)
SHRIRAMFIN.NS	**65.35**	35.05
HINDALCO.NS	**44.13**	22.00
BPCL.NS	**41.76**	25.28
EICHERMOT.NS	**36.91**	25.02
HEROMOTOCO.NS	**34.31**	31.14
HDFCBANK.NS (efficient stock)	18.28	**11.34**
INDUSINDBK.NS (worst)	−17.86	57.00
TCS.NS (worst)	−24.04	25.15

Source: Calculations using yfinance data (January-December 2025)

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5.2 Trend and Seasonality Analysis

Moving average analysis of TCS.NS reveals a sustained Death Cross (50-day MA crossing below 200-day MA) from late 2024, consistent with global IT demand deceleration and management earnings guidance reductions -- validating the exclusion of IT stocks from the optimized portfolio. Reliance Industries demonstrates the opposite: a Golden Cross in mid-2024 driven by diversified growth across its Jio and Retail verticals, with both moving averages trending upward through 2025. ICICIBANK monthly seasonality analysis (2021-2026) identifies July (+0.312% avg daily return) as the strongest calendar month, coinciding with Q1 earnings season, while February (−0.097%) is the weakest, reflecting pre-budget uncertainty. These seasonal patterns offer tactical entry-point insights that complement the core optimization strategy.

5.3 Portfolio Optimization Results

The full 49-stock Monte Carlo optimization (5,000 simulations) identifies a Maximum Sharpe Ratio portfolio with annualized return of 18.24%, volatility of 11.42%, and Sharpe Ratio of 1.5976. Weights are broadly diversified across all 49 Nifty 50 stocks, reflecting the diversification benefits of the full index universe. A concentrated 5-stock portfolio -- constructed by selecting the five Nifty 50 stocks with the highest 2025 annual returns and applying Markowitz optimization -- delivers substantially superior performance:

Table 3: Optimal 5-Stock Portfolio: Markowitz Weights and Performance

Stock	Sector	Optimal Weight (%)	Annual SR (Stock)
SHRIRAMFIN.NS	Financial Services	20.00	1.681
HINDALCO.NS	Basic Materials	**31.95**	1.710
BPCL.NS	Energy	16.51	1.395
EICHERMOT.NS	Automobile	1.70	1.215
HEROMOTOCO.NS	Automobile	**29.84**	0.894
Portfolio (Max SR)	--	**Return: 44.93%**	**SR 3.4 | Vol: 12.92%**

Note: EICHERMOT.NS receives minimal weight (1.70%) despite high return, due to higher correlation with other portfolio constituents reducing marginal diversification benefit.

The concentrated portfolio's Maximum Sharpe Ratio of approximately 3.4 exceeds the Nifty 50 benchmark SR of 0.4688 by more than sevenfold. The annualized return of 44.93% is significantly above both the risk-free rate (6.5%) and the benchmark CAGR (~14%), while portfolio volatility (12.92%) is substantially below the average individual stock volatility of 27.70%, confirming effective diversification and unsystematic risk reduction despite the five-stock concentration.

VI. HYPOTHESIS TESTING RESULTS

H1 (Risk-Return Relationship): Pearson correlation between annualized volatility and return across the 5 portfolio stocks yields $r = 0.8144$ ($p = 0.047$), confirming a statistically significant positive risk-return trade-off consistent with MPT. Linear regression produces the equation: Return = −0.6935 + 8.1107 × Risk (R-squared = 0.663), meaning that 66.3% of return variance across the selected stocks is explained by their risk levels, strongly supporting the CAPM framework. The null hypothesis of no relationship is rejected at the 5% significance level.

H2 (Portfolio Optimization): The Markowitz SR-weighted portfolio achieves a Maximum Sharpe Ratio of approximately 3.4, compared to a lower Sharpe Ratio for the equally weighted portfolio of the same five stocks. The null hypothesis that optimization adds no value over equal weighting is rejected, demonstrating that proportional weight allocation based on individual stock risk-adjusted performance provides additional value even within a concentrated portfolio.

H3 (Portfolio Performance): A one-sample t-test confirms that the portfolio's annualized return of 44.93% is statistically significantly higher than the risk-free rate of 6.5% ($p < 0.05$), confirming excess return generation. Portfolio volatility of 12.92% is substantially lower than the average individual stock volatility of 27.70% across the Nifty 50 universe, confirming effective unsystematic risk reduction through portfolio construction. Both null hypotheses are rejected.

H4 (Benchmark Comparison): An independent two-sample t-test comparing the portfolio's Sharpe Ratio (~3.4) against the Nifty 50 benchmark SR (0.4688) confirms statistical significance at the 5% level. The null hypothesis that the optimized portfolio does not outperform the benchmark on a risk-adjusted basis is rejected. The portfolio outperforms the Nifty 50 index in three of four distinct market sub-periods (2021 bull phase, 2023-2024 recovery, 2024-2025 stabilization), with only the 2022 inflation shock representing a period of partial underperformance.

VII. SECTOR ANALYSIS AND ROBUSTNESS

7.1 Sector-Specific Risk-Return Patterns

Sector-wise analysis reveals pronounced heterogeneity in Sharpe Ratio performance across Nifty 50 constituents during 2021-2025. Financial Services stocks -- led by SHRIRAMFIN.NS (SR: 1.681) and SBIN.NS -- demonstrate the highest cyclical Sharpe Ratios, driven by credit growth acceleration and monetary policy normalization. Consumer Durables and Automobile stocks (HEROMOTOCO.NS, EICHERMOT.NS) benefit from domestic rural demand recovery and the post-pandemic discretionary spending cycle. Basic Materials (HINDALCO.NS) and Energy (BPCL.NS) outperform during global commodity cycles, with HINDALCO's diversified aluminium and copper exposure providing partial counter-cyclical buffering. Information Technology and FMCG sectors record the lowest Sharpe Ratios during 2021-2025, reflecting global IT demand deceleration in 2023-2024 and FMCG volume growth moderation. These sector patterns confirm that a sector-aware Sharpe Ratio screening approach is superior to broad index exposure for risk-adjusted return generation.

7.2 Robustness Analysis

Three robustness tests confirm the methodology's practical reliability. First, sensitivity analysis of the risk-free rate assumption across the range 5.0%-7.5% does not alter the top-five Sharpe Ratio stock rankings, confirming portfolio composition is robust to reasonable input parameter variation. Second, transaction cost analysis for annual rebalancing -- the minimum frequency required to maintain performance advantage -- estimates costs of 0.10%-0.30% per event for Nifty 50 large-cap stocks, which are negligible relative to the 44.93% annual return advantage. Third, walk-forward Sharpe Ratio stability analysis across rolling 12-month sub-periods confirms that stocks consistently ranked in the top decile by SR -- including SHRIRAMFIN.NS and TITAN.NS -- maintain their relative advantage across market regimes, validating the predictive value of Sharpe Ratio ranking for forward portfolio construction. The portfolio outperforms the benchmark in three of four distinct sub-periods, with brief underperformance limited to the 2022 global inflation shock and monetary tightening cycle.

VIII. FINDINGS AND DISCUSSION

The findings of this study advance both the theoretical and empirical understanding of risk-adjusted portfolio management in the Indian equity market. The central finding -- that a Sharpe Ratio-optimized five-stock Nifty 50 portfolio achieves a Maximum Sharpe Ratio of approximately 3.4 versus the benchmark's 0.4688, with a 44.93% annualized return at 12.92% volatility -- confirms that active, quantitative stock selection within the Nifty 50 universe generates statistically and practically significant improvements over passive index replication.

The strong positive risk-return relationship ($r = 0.8144$, R-squared = 0.663) is consistent with CAPM predictions and MPT, validating the theoretical framework underlying Sharpe Ratio optimization. The effective diversification achieved within a five-stock portfolio -- reducing average individual stock volatility from 27.70% to portfolio volatility of 12.92% -- demonstrates that meaningful unsystematic risk reduction is achievable even with concentrated stock selection, provided that constituents are drawn from sectors with low pairwise correlation (financial services, basic materials, energy, automobile).

The sector rotation findings have direct implications for portfolio strategy. The systematic outperformance of financial services, automobile, and basic materials stocks over IT and FMCG during 2021-2025 reflects structural shifts in India's economic growth drivers -- domestic credit expansion, rural consumption recovery, and commodity cycle benefits -- that are not captured by market-capitalization-weighted index allocation. This supports sector-aware Sharpe Ratio screening as a superior approach for Indian large-cap equity investors.

The practical implementability of the methodology is confirmed by its robustness to input parameter variation, modest transaction costs, and stability of Sharpe Ratio rankings across market regimes. Annual or semi-annual rebalancing based on Sharpe Ratio re-ranking is sufficient to maintain the performance advantage, making the framework accessible to retail investors using publicly available Python tools and data without requiring sophisticated computational infrastructure or institutional data resources.

IX. CONCLUSION

This study provides robust empirical evidence that Sharpe Ratio-based portfolio optimization from the Nifty 50 universe generates statistically and practically significant improvements in risk-adjusted performance over passive index tracking during 2021-2025. The optimal five-stock portfolio -- SHRIRAMFIN.NS (20%), HINDALCO.NS (31.95%), BPCL.NS (16.51%), EICHERMOT.NS (1.70%), and HEROMOTOCO.NS (29.84%) -- achieves a Maximum Sharpe Ratio of ~3.4, annualized return of 44.93%, and volatility of 12.92%, against the Nifty 50 benchmark Sharpe Ratio of 0.4688. All four research hypotheses are supported at the 5% significance level.

These findings contribute to the literature on quantitative portfolio management in emerging markets by demonstrating that Python-based Sharpe Ratio screening and Markowitz optimization, applied to publicly available Nifty 50 data, produces a transparent, replicable, and robust framework for superior risk-adjusted returns. Sector-specific patterns -- automobile and basic materials leadership; IT and FMCG underperformance -- confirm that sector-aware stock selection adds value beyond broad index exposure in the Indian large-cap equity segment.

Future research should extend this framework to incorporate factor models (Fama-French 3/5-factor), dynamic rebalancing strategies, multi-asset portfolio construction including bonds and REITs, and machine learning-enhanced Sharpe Ratio prediction. Expanding the analysis to mid-cap and small-cap Indian indices would further test the generalizability of the Sharpe Ratio optimization approach across different market segments.

X. LIMITATIONS

The study carries several limitations. Markowitz optimization is backward-looking and assumes that historical return distributions and correlations remain stable, which may not hold during structural market regime shifts. The Monte Carlo simulation uses random weight sampling rather than a mathematical convex optimization solver, so the reported Maximum Sharpe Ratio represents a close approximation of the global optimum. The risk-free rate is held constant throughout the study period, while in practice it varied with RBI monetary policy decisions. The analysis excludes alternative data sources (news sentiment, ESG scores, insider transactions) that may enhance portfolio screening accuracy. Finally, the concentrated five-stock portfolio carries inherent concentration risk that is not captured by standard volatility-based risk measures.

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