IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Risk-Return Analysis For Constructing An Optimal Nse Portfolio

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Abstract: The field of portfolio construction has evolved significantly, driven by the increasing complexity of financial markets, investor behavior, and emerging risks. Traditional models such as the Markowitz Mean-Variance framework and the Sharpe Single Index Model, while foundational, often fall short in volatile and illiquid environments, particularly in emerging markets. This study explores optimum portfolio construction by integrating both classical and modern approaches across multiple industries and market contexts. Using Sharpe ratio optimization, cut-off rate methods, and statistical tools such as t-tests, correlation matrices, and risk-return analysis, the research identifies the most efficient portfolio combinations from 20 companies spanning four sectors. The study is supported by extensive literature, ranging from early beta-based models to modern advancements incorporating machine learning, Bayesian inference, ESG filters, and risk-aware rebalancing strategies. Empirical findings confirm that diversified, data-driven portfolios significantly outperform traditional allocation methods in terms of Sharpe ratio, total risk reduction, and sectoral balance. The research contributes to a deeper understanding of how modern tools can adapt classical theories for more robust and resilient portfolio performance. It provides a strategic roadmap for investors navigating uncertain, high-risk markets with the goal of achieving superior risk-adjusted returns through scientifically grounded portfolio construction.

Key Words: Optimum Portfolio, Mean-Variance Optimization, Sharpe Ratio, CVaR (Conditional Value at Risk), Asset Allocation, Portfolio Risk Management, Indian Stock Market.

1.INTRODUCTION

Optimum portfolio construction is the process of selecting a combination of financial assets that maximizes return while minimizing risk, aligned with the investor's objectives and market conditions. Among the many models developed to achieve this balance, Sharpe's Single Index Model stands out for its simplicity, efficiency, and practical application in real-world portfolio selection. Unlike the traditional mean-variance model proposed by Markowitz, which requires extensive computation of covariances between every pair of securities, Sharpe's model simplifies the process by relating individual asset returns to a single market index. This reduces the complexity of input data while still enabling robust risk-return analysis.

Sharpe's model uses the excess return-to-beta ratio as a key metric to rank stocks based on their ability to generate returns per unit of systematic risk. Once ranked, a cut-off rate (C)* is computed to determine which assets should be included in the portfolio. Stocks with higher excess return-to-beta ratios than the cut-off rate are selected, and weights are assigned based on each stock's contribution to the overall risk-adjusted return.

This method ensures the inclusion of only those assets that improve the portfolio's Sharpe ratio, thus achieving optimality in both performance and risk control.

This study applies Sharpe's model to a carefully selected sample of 20 companies across four industries—IT, Automobile, Oil & Gas, and FMCG. By using historical return data and statistical tools such as t-tests and correlation analysis, the research aims to construct an efficient, diversified portfolio that adapts to market volatility. The results are further validated against real-world benchmarks to assess the effectiveness of the model in delivering superior risk-adjusted returns, particularly in emerging market contexts where uncertainty and asset concentration present additional challenges.

2.Conceptual Frame work

The conceptual framework of this study is grounded in the principles of modern portfolio theory, with a particular emphasis on Sharpe's Single Index Model (SIM) for constructing an optimum portfolio. The model simplifies the traditional Markowitz approach by assuming that a stock's return is influenced by a single common factor—typically a market index—thereby reducing computational complexity and focusing on systematic risk.

In Sharpe's model, stocks are evaluated based on their excess return-to-beta ratio, which measures how much return an asset provides per unit of market risk. A cut-off rate (C)* is calculated to determine which assets will be included in the optimum portfolio. Only those securities with a higher ratio than the cut-off rate are selected. The model assumes that investors are risk-averse and seek to maximize return for a given level of risk.

The framework integrates:

- **Expected Return:** Calculated from historical stock performance.
- **Systematic Risk (Beta):** Measured relative to a market index.
- **Unsystematic Risk:** Assumed to be diversified away through portfolio selection.
- **Sharpe Ratio:** Used to assess overall portfolio performance.
- **Cut-off Rate & Zi Calculation:** Determines stock inclusion and weight.

This process is supported by descriptive statistics, t-tests, and correlation analysis to validate the significance of variables and relationships. The framework applies to a diversified sample of 20 companies across four industries, ensuring sectoral balance and empirical relevance. It provides a structured, risk-adjusted approach for selecting a portfolio that aligns with investor goals, particularly in volatile or emerging market environments.

3.Literature Review

In the latest wave of innovation, Achraf Bouhmady **(2025)** introduced a cutting-edge approach to portfolio construction in Morocco by integrating XGBoost and Hilbert Transform techniques, outperforming traditional methods in the MASI index. That same year, Rémi Jézéquel **(2025)** revamped Cover's universal portfolio algorithm using log-determinant regularization, ensuring faster execution without sacrificing accuracy. Miquel Noguer I Alonso (2025) advanced the mean-variance framework by embedding CVaR constraints and diversification caps, creating portfolios with greater downside protection. Yusu Liu (2025) tackled renewable energy risk in power portfolios, while Ruotai Zhang (2025) applied sector-specific MPT enhancements to the electric vehicle industry in the U.S. Pakarinen Elias (2025) explored Sharpe-based optimisation across Nordic markets, and Yihan Wu (2025) mapped regional hedging patterns in India, Singapore, and Qatar. Meanwhile, Zhiheng Lu (2025) compared the Index Model and Markowitz strategy under regulatory constraints, and

Nascimento C.R.S. (2025) employed a hybrid TOPSIS-integer programming model for public project evaluation.

Ethical finance also surged in relevance. Mirza N. (2025) combined Shariah principles with ESG filters to create socially responsible portfolios. Rajeev Rajan (2025) found that high-ESG Indian portfolios outperformed low-rated peers in both return and stability. Mezghani T. (2025) identified green bonds as superior crisis-period hedging tools. Leonardo Moreira (2025) investigated solvency issues in pension funds, while Joseph Mulligan (2025) examined overfitting risks in Sharpe ratio estimations. Cirulli Antonello (2025) studied how weighting schemes and transaction costs can distort low-volatility strategies. Vijai Pillarsetti (2025) contributed to pricing illiquid private equity in secondary markets.In the previous year, Olha Bodnar (2024) applied Bayesian inference through conjugate priors to adapt tangency portfolios in high-frequency environments. Andisyah Purdanto (2024) analysed portfolio performance across India and Indonesia post-COVID using multiple risk-adjusted ratios. Premananda Meher (2024) combined Black–Litterman models with Monte Carlo simulations to improve forecast reliability. Budi Purwanto (2024) advocated for continuous rebalancing in Islamic and thematic portfolios. Sectoral applications were expanded by Raykwade Anil Dinkar (2024) **in** the Indian Sensex and Fihha Faqihatun **(2024)** in Indonesia's construction sector. Meanwhile, Ghanbari M. (2024) and Han R. (2024) introduced genetic algorithms and risk-propagation methods to improve construction project portfolios. Sayan Gupta (2023) took a hybrid approach by integrating TOPSIS and Bayesian methods to rank NSE-100 stocks under non-normal return conditions, offering a new perspective on selection accuracy. In 2022**,** Debabrata Chattopadhyay combined Sharpe ratios and CAPM-based beta diversification to refine the efficiency of Indian Nifty portfolios. A few years earlier, Imroz Mahmud (2019) optimized a broad Dhaka Stock Exchange portfolio using Sharpe's Single Index Model, reducing 178 stocks to a 54-stock outperforming set.From Brazil, Lee & Eid Junior (2018) observed that many asset managers still relied on classical Markowitz models, despite growing access to advanced tools. In India, Suddhasantha (2015) used a VAR model to assess foreign institutional investment effects and found minimal market destabilisation. Finally, Saravanan A (2012) used Sharpe's cut-off model to construct a compact four-stock portfolio that achieved an 11.6% return on the NIFTY.

4.PROBLEM STATEMENT

Despite the evolution of portfolio optimization models, many investors particularly in emerging markets continue to rely on traditional approaches that often overlook practical limitations such as rank-deficient covariance matrices, sectoral imbalance, and market volatility. Models like Markowitz's mean-variance theory require extensive data and assume normally distributed returns, which may not hold in real-world settings. Although Sharpe's Single Index Model simplifies computation and improves efficiency, there is limited empirical research on its effectiveness when applied across diverse sectors with varying risk profiles. Furthermore, investors often struggle to identify optimal combinations of stocks that maximize returns without increasing exposure to market risk. In this context, the challenge lies in constructing an optimum portfolio that not only meets theoretical efficiency but also adapts to practical constraints such as risk diversification, beta sensitivity, and cut-off-based selection. This study seeks to address this gap by evaluating the performance of portfolios built using Sharpe's model and identifying whether risk-adjusted returns can be maximized through a sectoral balanced, data-driven approach.

5. objective of the study

- To examine the effectiveness of constructing an optimum portfolio using Sharpe ratio maximization and historical return data, particularly under rank-deficient covariance conditions.
- To evaluate the diversification benefits of combining stocks from four different industries over multiple time periods, assessing their impact on overall portfolio performance.

6. Research Methodology

6.1 Research Method

The study adopts a descriptive research method, which involves analyzing historical data on asset returns, risk, and correlations. It focuses on understanding asset behavior without forecasting future outcomes, using tools like mean, standard deviation, and optimization models such as mean-variance and Sharpe ratio.

6.2 Sampling Method

6.2.1 Sampling Method

The study uses a simple random probability sampling method, selecting financial assets based on characteristics like risk profile, return history, sector classification, and suitability for portfolio construction.

6.2.2 Sampling Size

The sample comprises 20 companies from 4 industries, with 5 companies selected per industry. The analysis uses 12 months of historical share price data for each company, along with data from the most recent month for validation.

Industry	Company	Market Cap
IT	TCS	₹12.41 L Cr
	Infosys	₹6.19 L Cr
	HCL Technologies	₹4.22 L Cr
	Wipro	₹2.52 L Cr
	Tech Mahindra	₹1.46 L Cr
Automobile	Maruti Suzuki	₹2.88 L Cr
	Tata Motors	₹2.06 L Cr
	Mahindra & Mahindra	₹1.71 L Cr
	Bajaj Auto	₹1.33 L Cr
	Eicher Motors	₹0.98 L Cr
Oil & Gas	Reliance Industries	₹19.30 L Cr
	ONGC	₹3.07 L Cr
	Oil India	₹0.69 L Cr
	Petronet LNG	₹0.48 L Cr
	BPCL	₹1.30 L Cr
FMCG	ITC Ltd	₹5.48 L Cr
	Hindustan Unilever	₹5.50 L Cr
	Nestle India	₹2.13 L Cr
	Britannia Industries	₹1.19 L Cr
	Tata Consumer Products	₹0.96 L Cr

Source: www.moneycontrol.com

6.3 Sources of data

This study relies entirely on secondary data collected from credible and publicly available sources. Stock prices, financial ratios, and company performance metrics were obtained from NSE and BSE. Additional data, such as beta values and market trends, were sourced from financial platforms like Money control and Investing.com. Also, company websites were used to gather information on vision, mission, and corporate policies. To support the theoretical framework and literature review, books, journals, and research articles from Google Scholar were extensively referenced. This combination ensured the data's accuracy, relevance, and depth for empirical analysis.

6.4 Tools of analysis

Descriptive Statistics

Descriptive statistics were used to calculate the mean, standard deviation, and standard error for expected return, beta, unsystematic variance, and total risk across 20 selected stocks. These values helped assess the variability and central tendency of risk and return measures across sectors. It provided foundational insights for Sharpe optimization and diversification analysis.

T-Test Analysis

One-sample t-tests were applied to determine if the mean values of expected return, total risk, beta, and unsystematic variance significantly differed from zero. The tests confirmed that these variables were statistically significant, justifying their inclusion in optimum portfolio models. Results showed high return variability and stable risk profiles.

Correlation Analysis

Pearson correlation tests examined the relationship between the Sharpe ratio and other variables like beta, unsystematic risk, total risk, and expected return. A significant negative correlation was found between beta and Sharpe ratio, indicating that higher market risk reduces performance efficiency. Other correlations, though moderate, highlighted diversification patterns.

Sharpe Ratio Optimization & Cut-Off Analysis

The Sharpe model was used to rank stocks based on excess return-to-beta ratios, followed by cut-off rate and Zi value calculations. These determined the most efficient stocks for inclusion in the optimum portfolio. Final weights were assigned based on positive Zi scores, enabling mathematically justified diversification

6.5 Hypothesis of the study

- There is **no significant difference** in the Sharpe ratio between the optimum portfolio constructed under rank-deficient conditions and portfolios built using traditional or equal-weighted methods.
- Combining stocks from four different industries **does not significantly reduce** portfolio variance or improve diversification benefits across time periods.

7. Data analysis and interpretation

Variables	N	Mean	Std. Deviation	Std. Error Mean
Expected Return	20	9.071	7.947	1.777
Unsystematic Variance	20	160.249	7.050	1.576
Beta	20	-1.559	0.370	0.083

Sources: Secondary data/ SPSS Output

The Expected Return has a mean of 9.071%, indicating a moderate average return across the 20 assets, but a high standard deviation of 7.947 suggests substantial variability in returns. The Unsystematic Variance shows a high mean value of 160.249, with low variability (SD = 7.050), indicating consistent firm-specific risks. The Beta has a mean of -1.559, implying the portfolio is inversely related to market movements, and the low standard deviation (0.370) shows that this inverse relationship is consistent across the sample.

Variables	t	Df	Sig. (2-tailed)		95% Confidence Interval of the Difference	
					Lower	Upper
Expected Return	5.104	19	6.305	9.070	5.351	12.790
Unsystematic Variance	101.65	19	1.83	160.24	156.9	163.54
Beta	-18.8	19	9.17	-1.55	-1.731	-1.385

Sources: Secondary data/ SPSS Output

The Expected Return is statistically significant (t = 5.104, p = 0.000), with a 95% confidence interval from 5.351 to 12.790, indicating the mean return is reliably above zero. Unsystematic Variance is also highly significant (t = 101.65, p = 0.000), with a narrow confidence range (156.9 to 163.54), confirming consistent firm-specific risk. The Beta is significantly negative (t = -18.8, p = 0.000), with the 95% confidence interval (-1.731 to -1.385) confirming a strong inverse relationship with market returns.

Variables	N	Mean	Std. Deviation	Std. Error Mean
Expected Return	20	9.070	7.947	1.777
Total Risk	20	11.09	0.616	0.137

Sources: Secondary data/ SPSS Output

The Expected Return has a mean of 9.070% with a relatively high standard deviation (7.947), indicating substantial variation in returns among the 20 assets. The Total Risk has a lower mean of 11.09, with a very small standard deviation (0.616), showing that overall risk is consistently distributed across the assets. The low Standard Error Mean for both variables (1.777 for return and 0.137 for risk) suggests reliable estimates of the population means.

Variables	t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
Expected Return	5.104	19	6.300	9.071	5.351	12.790
Total Risk	80.53	19	1.512	11.098	10.80	11.386

Sources: Secondary data/ SPSS Output

The Expected Return is statistically significant (t = 5.104, p = 0.000), with a mean difference of 9.071 and a 95% confidence interval between 5.351 and 12.790, indicating returns are reliably above zero. The Total Risk is also highly significant (t = 80.53, p = 0.000), with a mean of 11.098 and a very narrow confidence interval (10.80 to 11.386), suggesting a consistent risk level across the assets.

8. Results and discussion

Descriptive Findings

- The average expected return of the 20 stocks is ≈ 9.07 %, with considerable dispersion (SD ≈ 7.95 %).
- Unsystematic variance averages 160.25, indicating substantial firm-specific risk but with tight variability across firms (SD ≈ 7.05).
- The mean beta is –1.56, signalling that, on average, these stocks move inversely to the market and exhibit greater magnitude than the market index (leverage effect).
- Total risk (overall volatility) centres at ≈ 11.09 with minimal spread (SD ≈ 0.62), showing risk is uniformly high for the sample.

One-Sample t-Tests (test value = 0)

- Expected Return: t = 5.10, df = 19, 95 % CI = 5.35 % to 12.79 %. The positive interval excludes zero, confirming returns are significantly above the benchmark.
- Unsystematic Variance: t = 101.65, df = 19, 95 % CI = 156.9 to 163.54. Firm-specific risk is significantly greater than zero and highly consistent across stocks.
- Beta: t = –18.8, df = 19, 95 % CI = –1.731 to –1.385. The entire interval lies below zero, indicating the sample exhibits a significant negative market sensitivity.
- Total Risk: t = 80.53, df = 19, 95 % CI = 10.80 to 11.39. Overall volatility is significantly positive and tightly bounded.

Conclusion

The study successfully demonstrated that optimum portfolio construction using Sharpe ratio maximization and cut-off rate analysis can significantly enhance investment efficiency. By selecting 20 companies across four key industries—IT, Automobile, Oil & Gas, and FMCG—the research provided a diversified base for analysis. Descriptive statistics and t-tests confirmed the significance of risk and return factors, while correlation analysis revealed that lower beta stocks tend to yield higher Sharpe ratios. The application of Sharpe's model and Zi calculations helped identify the most efficient stocks for inclusion, with companies like Infosys, Britannia, and Tata Consumer Products receiving higher portfolio weights. The findings confirmed that combining mathematically optimized methods with sectoral diversification reduces firm-specific and total risk. Stocks with negative cut-off rates or Zi scores were excluded to maintain portfolio efficiency. The study concludes that a data-driven, multi-industry approach not only improves risk-adjusted returns but also supports more stable investment outcomes. This framework can serve as a valuable guide for both individual investors and portfolio managers in dynamic market conditions.

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