



INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

A Study On Multifactor Based Stock Selection Method From The Universe Of Nifty 500

¹V Jeevan Kumar, ²S Satheesh Kumar

¹Student, ²Associate Professor

^{1,2}Master of Business Administration

^{1,2}Panimalar Engineering College, Chennai.

Abstract: This study proposes a dual-layered stock selection methodology applied to the NSE 500 universe. The first layer involves a multi factor model combining quality, value, momentum, and low volatility factors. The top 50 multi factor scoring stocks are further filtered through correlation matrix analysis, eliminating stocks with high pairwise correlations. Among each correlated pair ($r > 0.50$), the stock with the lower Sortino Ratio is removed. The final 25-stock portfolio is constructed using equal weighting. The study evaluates the portfolio's performance against market benchmarks using risk-adjusted metric i.e., sharpe ratio. Results indicate superior diversification and downside risk optimization through this systematic selection process.

Index Terms - Multi factor investing, NSE 500, stock selection, correlation filtering, Sortino ratio, portfolio construction, sharpe ratio.

I. INTRODUCTION

The increasing breadth of the Indian stock market presents a challenge in identifying high-potential stocks for investors. Relying solely on a single-factor or subjective judgment often leads to suboptimal choices. This study proposes a dual-layer methodology—first, a multifactor scoring model to evaluate stocks on a quantitative basis, and second, a correlation-based filter to remove overlapping returns. The final output is a refined set of 25 stocks selected from the NSE 500 universe, offering strong fundamentals and minimized correlation, aimed at better risk-adjusted portfolio performance.

II. LITERATURE REVIEW

Haiwen Liu, Yongxin Chen, 2023. Quantitative investments are flourishing due to advancements in mathematics and behavioral finance theory. Quantitative investment is becoming increasingly common in today's culture. This study uses a multi-factor stock selection model to examine financial indicators and trading data of listed businesses using quantitative approaches. Shuiyingzi Hu, Pai Peng, and Mingwei Xu, 2023. To investigate trade data from stock exchanges such as Shanghai and Shenzhen 300 and Shanghai Securities last year, select criteria such as market capitalization, ROE, EPS, P/E, and turnover were examined. Use quantitative tools to develop multi-factor stock picking strategies. Aditya Maheshwari, Traian A. Pirvu, 2020. The framework is a multi-period stochastic financial market with a single tradable stock, stochastic income, and a non-trading index. At some benchmark time horizon, the correlation requirement is applied to both the portfolio and the non-tradable index. Vaibhav Lalwani, Madhumita Chakraborty, 2018. This study explores whether stock selection strategies based on four fundamental quality indices outperform the broader Indian market. Portfolios were built using equities from the BSE-500 index, ranked by quality, and tested against the market. Qing Ye, 2021. This study uses Gordon's dividend growth model to derive four variables and create an evaluation index system for quality characteristics based on 12 secondary indicators of profitability, growth, safety, and dividend distribution.

2.2 OBJECTIVES

- To study on multifactor based stock selection method from the universe of NSE 500 stocks.
- To identify high quality, undervalued, momentum driven and low volatility stocks using a multi factor scoring model.
- To reduce portfolio risk by eliminating highly correlated stocks and through downside risk filtering.
- To evaluate the portfolio's risk adjusted performance against the benchmark.

2.3 SCOPE OF THE STUDY

This study is confined to developing a multifactor-based stock selection model with the NSE 500 index as the investment universe. It employs four essential factors—quality, value, momentum, and low volatility—to evaluate and rank stocks using standardised Z-scores. The study focuses on filtering fundamentally weak and highly connected equities to provide diversity and robustness. The study uses quantitative screening, composite scoring, correlation matrix filtering to construct a portfolio of 25 equities. Performance is evaluated using risk-adjusted indicators such as the Sharpe ratio. The study uses publicly available financial data and assumes a medium- to long-term investment horizon.

III. RESEARCH METHODOLOGY:

3.1 Data collection and sampling design.

The study examines 350 NSE 500 equities, filtering for data completeness and liquidity. The secondary datas are obtained from NSE for the period of 2020 to 2025. and further Financial data was obtained from the NSE, Screener.in, Yahoo Finance, and Trendlyne.

3.2 Multifactor model.

The composite score for each stock is calculated by adding Z-scores from four factors: quality, value, momentum, and low volatility, with weights determined by the portfolio strategy. The composite score is calculated using the formula below:

$$\text{Multifactor Score} = (0.35 \times Z_{\text{Quality}}) + (0.25 \times Z_{\text{Value}}) + (0.25 \times Z_{\text{Momentum}}) + (0.15 \times Z_{\text{Low Volatility}}).$$

The quality score is one of the multi factor model's metrics that focuses on analyzing fundamentally good or financially healthy firms. Metrics used to determine quality score are ROE, EPS growth, and D/E ratio., Value score is one of the key metrics in the multi factor model. It is used to identify stocks that are potentially undervalued based on their fundamental ratios. Investors who follow value strategies believe these stocks are trading for less than their intrinsic value and may offer superior long-term returns. Metrics used to measure value score in this study are. P/E, P/B, P/S, and dividend yield, Momentum score identifies stocks that have shown positive price trends in recent periods, based on the belief that such trends may continue in the short to medium term. Momentum investing is rooted in behavioral finance, as it captures investor sentiment and herd behavior. And the momentum factor metrics are 6-month and 12-month returns. Low Volatility score is an essential part of the multi factor model, which aims to identify stocks that demonstrate price stability over time of one year. The core idea behind this factor is based on the concept that less volatile stocks tend to provide better risk-adjusted returns in the long run, especially during periods of market stress or uncertainty. Unlike momentum which favors high returns, low volatility focuses on return consistency and risk control. Low volatility used metrics are Standard deviation of returns. To rank the stocks, each metric was standardized into Z-scores and then aggregated into a composite score. The top 50 stocks were shortlisted.

3.3 Correlation and Sortino based filtering.

A Pearson Correlation Matrix was build for the top 50 stocks based on Mutlifactor score and further filtering removed firms with return correlations greater than 0.5 based on lower Sortino Ratios, to ensure the diversification and risk based filtering and this process resulting in a selection of 25 diversified stocks.

Sortino ratio = $\frac{r_p - r_f}{\sigma_p}$. (r_p = portfolio return, r_f = risk free rate., σ_p = downside risk.).

3.4 Portfolio construction and performance evaluation.

Each stock in the final portfolio received an equal weight. Expected risk and returns were determined for one, three, and five years. Risk adjusted performances were founded using sharpe ratio.

Sharpe ratio = $\frac{r_p - r_f}{\sigma_p}$. (r_p = portfolio return, r_f = risk free rate., σ_p = overall risk (SD)).

IV. DATA ANALYSIS AND INTERPRETATION.

TABLE 4.1 TOP 10 STOCKS BASED ON MULTIFACTOR SCORE.

STOCKS	QUALITY SCORE	VALUE SCORE	MOMENTUM SCORE	LOW VOLTALITY SCORE	MULTIFACTOR SCORE
JSWHL	-0.258	0.169	6.688	-1.179	1.447
PGEL	1.662	-0.818	4.894	-1.463	1.381
REDINGTON	0.311	3.354	0.864	-0.537	1.083
BANKBARODA	1.181	2.706	-0.150	0.024	1.056
INDIANB	1.099	1.929	0.423	-0.121	0.955
ICICIBANK	0.653	-0.018	1.239	2.557	0.917
PNB	1.302	2.213	-0.444	-0.045	0.891
HDFCBANK	0.430	0.126	1.228	2.588	0.877
ONGC	0.338	3.446	-0.428	-0.114	0.856
KARURVYSYA	1.159	1.006	0.557	0.196	0.826

Inference : Table 1 shows the top ten stocks picked using the multifactor composite scoring methodology. These companies were ranked top using a weighted combination of quality, value, momentum, and low volatility considerations. Standardized Z-scores were used to calculate the scores, which were then allocated factor weights. Although the whole model identified the top 50 stocks, just the top 10 are included here for brevity. This table shows how JSWHL, PGEL, REDINGTON, and others performed consistently across several variables, validating their inclusion in the initial layer of filtering.

TABLE 4.2 TOP 25 STOCK PORTFOLIO OF CORRELATION AND SORTINO BASED FILTERING.

STOCKS	Industry	SORTINO	Correlation filtered >0.5
JSWHL	Financial Services	1.986946794	no
PGEL	Consumer Durables	5.208562163	no
REDINGTON	Services	0.7353348394	no
INDIANB	Financial Services	1.02870112	yes
KARURVYSYA	Financial Services	0.73771507	yes
COROMANDEL	Chemicals	1.116751619	no
MUTHOOTFIN	Financial Services	0.5181161878	yes
EICHERMOT	Automobile and Auto Components	0.5461082174	no
GESHIP	Services	0.5742115135	no
ABBOTINDIA	Healthcare	0.6132982771	no
BAJAJHLDNG	Financial Services	0.6807515852	no

COALINDIA	Oil Gas & Consumable Fuels	0.2275882959	no
PFC	Financial Services	0.7923194036	yes
MARICO	Fast Moving Consumer Goods	0.4902276094	no
SUNPHARMA	Healthcare	1.371925981	no
LTFOODS	Fast Moving Consumer Goods	2.010440145	no
PAGEIND	Textiles	0.3234286291	no
DIVISLAB	Healthcare	0.7951717486	no
DRREDDY	Healthcare	0.4702001161	no
ECLERX	Services	1.292920478	no
NATIONALUM	Metals & Mining	0.5760478193	yes
KIMS	Healthcare	1.648215483	no
HCLTECH	Information Technology	0.5862415239	yes
MAZDOCK	Capital Goods	3.431209694	no
CHAMBLFERT	Chemicals	0.872099389	no

Inference: The final 25-stock portfolio was built applying a dual-layer filtering process, initially through multifactor scoring and subsequently refined through correlation analysis with Sortino Ratio comparisons. Stocks with a correlation coefficient larger than 0.5 were reviewed in pairs, and the one with the lowest Sortino Ratio was removed to reduce redundancy and improve downside risk control. As seen in the table, most retained stocks either had a low correlation with others or had a greater risk-adjusted return (higher Sortino Ratio) in correlated pairs. For example, PGEL (Sortino: 5.21) and MAZDOCK (3.43) were preserved despite correlation conflicts, whereas equities like INDIANB and MUTHOOTFIN were screened in from high-correlation pairs due to better risk-adjusted performance.

TABLE 4.3 RISK ADJUSTED PERFORMANCE OF MULTIFACTOR PORTFOLIO AGAINST BENCHMARK.

Time Frame	Metric	Multifactor Portfolio	
1-Year	Return	0.4508841103	0.120650128
	Standard Deviation	0.187326	0.1589808636
	Risk-Free Rate	0.07	0.07
	Sharpe Ratio	2.033268795	0.3185926083
3-Year	Return	0.374032273	0.1407519314
	Standard Deviation	0.167618	0.1487558924
	Risk-Free Rate	0.07	0.07
	Sharpe Ratio	1.813840238	0.4756243955
5-Year	Return	0.386847944	0.1882846841
	Standard Deviation	0.19005489	0.1863731083
	Risk-Free Rate	0.07	0.07
	Sharpe Ratio	1.66713913	0.634666048

Inference: Over 1, 3, and 5 years, the multifactor portfolio consistently beat the risk-adjusted NSE 500 benchmark. The portfolio had Sharpe ratios of 2.03, 1.81, and 1.67 for the relevant time periods, compared to the benchmark's 0.32, 0.48, and 0.63. This persistent outperformance demonstrates great recent returns, ongoing alpha creation, and successful long-term risk management strategies. These findings support the usefulness of the multifactor stock selection technique paired with correlation-based risk reduction, confirming the portfolio's superior risk-adjusted performance throughout short, medium, and long time periods.

V. .SUMMARY OF FINDINGS

- Multifactor score based leading to a top-50 list featuring JSWHL (1.447), PGEL (1.381), and Redington (1.083). Banking stocks were prominent, but the portfolio also included technology, pharmaceutical, and industrial names, resulting in a more diverse profile.
- A correlation matrix was used to filter the top 50 equities, removing those with correlations greater than 0.5 and lower Sortino ratios. BANKBARODA, PNB, AXISBANK, SBICARD, and HDFCBANK were among the stocks that were eliminated, resulting in reduced redundancy and increased diversity.
- After screening and ranking, a 25-stock equal-weight portfolio was created. the predicted portfolio returns were for 1-Year period 45.09%, for 3-Year period 37.40%, for 5-Year period 38.68%.
- The portfolio risk was assessed using the 25×25 covariance matrix, resulting in standard deviations of 1-Year is 18%, 3-Year is 16%, 5-Year is 19%. This shows a broadly distributed risk profile, assisted by equal weighting and correlation filtering.
- After screening and ranking the portfolio's risk-adjusted performance against the NSE 500 benchmark is as follows: Sharpe Ratios: Portfolio - 2.03 (1 year), 1.81 (3 years), 1.67 (5 years), vs. Benchmark - 0.32 (1 year), 0.48 (3 years), 0.63 (5 years).

VI. SUGGESTIONS

- Future iterations can explore dynamic factor weighting, in which criteria such as momentum are given greater weight during bullish market stages and factors such as quality are stressed during bearish market periods, allowing the model to adjust to changing market conditions.
- Sector diversification should be addressed in future models by incorporating sector caps or employing sector-neutral scoring methodologies to achieve more balanced representation across industries rather than permitting financial domination.
- Backtesting and rebalancing are critical for determining the model's resilience. Implementing regular rebalancing regimens, such as quarterly or semi-annual changes, would aid in achieving optimal portfolio alignment and performance over time.

VII. . CONCLUSION

This study indicates that a structured, dual-layer stock selection technique, which combines multifactor scoring with correlation matrix-based filtering, can provide a superior equity portfolio. By adding both return quality and downside risk awareness (Sortino), the final portfolio consistently outperforms its benchmark. The equal-weight technique ensures simplicity while keeping diversity. To improve accuracy, future studies may use dynamic weighting or machine learning methods.

VIII. BIBLOGRAPHY

REFERENCE

1. Yousefi et al. (2018) – “The Impact Made on Project Portfolio Optimisation by the Selection of Various Risk Measures”.
2. Brandtner and Kursten (2015) – Decision Making with Expected Shortfall and Spectral Risk Measures.
3. A Multi-Criteria Based Stock Selection Framework in Emerging Market" by Sanjib Biswas, Gautam Bandyopadhyay, Dragan Pamucar, and Neha Joshi 2022.
4. Quality Investing in the Indian Stock Market" by Vaibhav Lalwani and Madhumita Chakraborty, 2018.

5. Stock Selection Model Based on Quality Factor: Evidence from Chinese A-share Market by Qing Ye, 2021.
6. An Index Approach to Factor Investing in India, Jason Ye, CFA Director Strategy Indices, 2022.

WEBSITES

www.nseindia.com/products-services/indices-nifty500-index.

screener.in.

trendlyne.com

trading.com

jrps.shodhsagar.com

