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Evaluating a Rule-Based Multi-Factor Sector Rotation Strategy in the Indian Equity Market: A Historical Backtesting Approach

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Abstract

This study evaluates whether a rule-based, multi-factor sector-rotation strategy, adapted from a practitioner-oriented top-down equity-research framework, improves risk-adjusted performance relative to a broad Indian equity benchmark. Using the Nifty Bank, Nifty IT and Nifty Auto indices alongside the Nifty 100, the strategy ranks sectors quarterly on earnings growth, valuation and relative momentum and holds the two highest-ranked sectors. The factor rules were specified using a development period (January 2011–March 2018) and evaluated over a test period (April 2018–September 2026). In the test period, the strategy generated an annualised return of 16.7% and a Sharpe ratio of 0.56, compared with 10.1% and 0.27 for the Nifty 100 price-return index, after assumed trading costs. However, bootstrap tests did not establish statistically significant Sharpe-ratio differences against the benchmark ($p = 0.07$) or an equal-weight portfolio of the same sectors ($p = 0.08$); none of the primary hypotheses remained significant after Holm adjustment. The strategy also could not be distinguished from a momentum-only rule. Excess performance was concentrated around 2020–2021, was absent in the development period and was sensitive to factor weights. Given the three-sector universe and data limitations, these findings are exploratory and do not establish a persistent sector-rotation premium.

Keywords: sector rotation; multi-factor investing; momentum; valuation; backtesting; Indian equity market; Sharpe ratio

JEL classification: G11, G12, G14

1. Introduction

Portfolio managers often adopt a top-down approach, ranking sectors by earnings prospects, valuation and recent price strength before selecting individual securities. Such judgement-based frameworks are not always evaluated using historical tests that isolate the contribution of each signal and account explicitly for transaction costs. This study translates one practitioner-oriented framework, encountered during an internship at a portfolio-management firm in Pune, into a set of explicit rules and examines whether the resulting strategy improves risk-adjusted performance relative to a broad market benchmark and simpler alternatives. The firm's name should be included only in the form permitted by written clearance.

The contribution is deliberately narrow. The analysis does not test the framework's stock-selection or news-sentiment components because the historical data available for this study were insufficient to reconstruct them reliably without potential look-ahead or survivorship bias. Instead, it evaluates a sector-level implementation using three NSE sector indices. The rules were fixed before the designated test period, and the analysis reports uncertainty and robustness checks alongside point estimates.

The paper proceeds as follows. Section 2 defines the research problem and gap; Section 3 reviews relevant literature; Section 4 outlines the theoretical foundation; Section 5 presents the objectives and hypotheses; Sections 6–8 describe the data, factor model and backtesting design; Sections 9–12 report and interpret the results, implications and limitations; and Section 13 concludes.



Figure 1. Research design and portfolio-construction workflow.

2. Research problem and research gap

Research problem. Practitioner sector-rotation frameworks combine fundamental, valuation and price-trend information, often through discretionary judgement. Whether a rule-based implementation improves performance relative to a broad benchmark—and relative to holding the same sectors in equal weights—must be assessed empirically, taking transaction costs, data quality and sample period into account.

Research gap. In the literature reviewed for this study, momentum and value are often examined as separate signals, and much of the foundational evidence uses US data. The Indian studies considered here focus mainly on momentum, contrarian strategies and factor construction. The reviewed sources did not identify a direct test of a quarterly sector-rotation rule combining earnings growth, valuation and momentum and comparing it with an equal-weight portfolio of the same sectors. This is a provisional assessment, not a claim that no such study exists

3. Literature review

Momentum. Jegadeesh and Titman (1993) report that buying past winners and selling past losers earned significant returns at holding periods of three to twelve months in US data, with part of the profit reversing over the following two years. Carhart (1997) shows that one-year momentum accounts for much of the apparent persistence in mutual fund returns, and adds a momentum factor to a three-factor model. Moskowitz and Grinblatt (1999) document a strong momentum effect in industry returns that accounts for much of individual-stock momentum, and find industry momentum strategies profitable after controlling for size, book-to-market and stock momentum. This last result is the closest analogue to a sector-rotation rule and motivates the momentum signal used here.

Value and fundamentals. Fama and French (1993) relate average returns to market, size and book-to-market factors. Piotroski (2000) shows that simple accounting signals separate stronger from weaker firms within a high book-to-market group. These studies motivate combining valuation with an earnings measure rather than ranking on valuation alone. Both use US data, so their findings are not assumed to hold in India.

Evidence from India. Sehgal and Balakrishnan (2002) examine contrarian and momentum strategies in the Indian capital market. Agarwalla, Jacob and Varma (2013) construct factor returns for Indian equities using CMIE Prowess data, with attention to illiquidity and survivorship

Sector rotation. Conover, Jensen, Johnson and Mercer (2008) examine rotation between cyclical and defensive sectors in relation to monetary conditions in the United States. This literature links sector allocation to macroeconomic regimes, whereas the present study ranks sectors using earnings growth, valuation and momentum. The approaches are related but not equivalent.

Inference and data mining. Ledoit and Wolf (2008) show that conventional Sharpe-ratio tests can be unreliable under heavy-tailed returns or serial dependence and propose a studentised time-series bootstrap for comparing Sharpe ratios. Harvey, Liu and Zhu (2016) argue that extensive data mining can make conventional significance thresholds too permissive when evaluating proposed factors. These concerns motivate the use of bootstrap inference and a multiple-testing adjustment in this study. Although the backtest code was frozen before the test slice was run, the framework itself was developed in 2026 with knowledge of historical market behaviour; the test should therefore not be interpreted as a fully independent prospective evaluation.



4. Theoretical foundation

Tests of excess returns jointly evaluate a strategy and the risk model used to assess it; positive abnormal performance may reflect mispricing, compensation for risk, or model misspecification (Fama & French, 1993). Momentum has been attributed, among other explanations, to gradual information incorporation and behavioural mechanisms, and industry-level momentum is one documented manifestation (Moskowitz & Grinblatt, 1999). Valuation signals are based on the proposition that securities priced cheaply relative to fundamentals may earn higher subsequent returns, although the relationship can vary across periods. Sector rotation also has a macroeconomic rationale because sectors differ in their sensitivity to business and monetary conditions. Concentrating in the highest-ranked sectors may improve returns if the signals are informative, but it also creates exposure and drawdown risks. These arguments motivate the hypotheses; they are not tested as separate causal mechanisms in this study.

5. Research objectives and hypotheses

The study has four objectives: (1) translate the sector-level framework into reproducible rules; (2) estimate net-of-assumed-cost performance over a designated test period; (3) assess the contribution of sector rotation and signal combination relative to simpler alternatives; and (4) evaluate statistical significance, economic relevance and robustness.

Hypotheses (all two-sided, on Sharpe ratios of monthly excess returns in the test period):

- **H1.** H0: the Sharpe ratio of the multi-factor rotation strategy (A) equals that of the Nifty 100 benchmark (D).
- **H2.** H0: the Sharpe ratio of A equals that of an equal-weight portfolio of the same sectors (E). This is the central test of whether rotation adds value beyond holding the sectors.
- **H3.** H0: the Sharpe ratio of A does not exceed that of a fundamental-only rule (B) or a momentum-only rule (C). The two paired p-values are combined by taking the larger.
- **H4.** Performance is not sensitive to the factor weights or to the top-one versus top-two selection (assessed descriptively).

Hypotheses H1–H3 form one family and are adjusted using Holm's sequential procedure. Holm (1979) reference.]\ Statistical significance is distinguished from economic relevance. Before the results were examined, economic relevance was defined as annual net active return of at least 2%, an information ratio of at least 0.3 and a one-way cost break-even of at least 50 basis points.

6. Data and methodology

Data. Daily closing levels, price-to-earnings (P/E), price-to-book (P/B) ratios and dividend yields for the Nifty 100, Nifty Bank, Nifty IT and Nifty Auto were obtained from NSE Indices in October 2026. Yahoo Finance prices were used for Nifty Bank and Nifty IT because corresponding NSE price files were not obtained; Nifty Auto prices came from NSE. The Nifty 100 total-return index (TRI) was used as a secondary benchmark. The series were aligned to the NSE trading calendar over 1 January 2009–30 September 2026 (4,398 observations where reported). Nifty Auto valuation data begin on 12 July 2011. File-audit findings are summarised in Appendix A. Month-end observations were used. Three month-end observations missing from the Yahoo-derived series (28 February 2015, 30 October 2016 and 29 March 2019) were forward-filled using the preceding available trading-day value; this treatment should be considered when interpreting the results.

Sample. The analysis includes three sectors—Bank, IT and Auto—for which the required data were available at the time of analysis. They were not selected based on observed performance; nevertheless, selection based on data availability limits the sample and generalisability.

Structural breaks in NSE valuation series. The implied book value (index level divided by P/B) rises on 29 September 2023 by approximately 25% for the Nifty 100, 19% for IT, 24% for Auto and 4.5% for Bank, while P/E does not move correspondingly. Secondary sources indicate that NSE may have changed the net-worth basis used in index P/B calculations from standalone to consolidated accounts on that date. The pre-break P/B series is adjusted by dividing by one plus the implied step, and an unadjusted version is included as a sensitivity analysis. Implied earnings (index



level divided by P/E) also show abrupt changes on 31 March 2021 across series and on 25 September 2019 for Bank, suggesting possible changes in P/E methodology that remain unverified.

7. Factor-model development

Three signals are computed at each month-end for each sector s:

- **Earnings growth (EG).** EG(s,t) = ln[EPS(s,t) / EPS(s,t-12)], where EPS = index level / P/E.
- **Valuation comfort (VAL).** VAL(s,t) = 100 minus the percentile rank of the break-adjusted P/B at t within the sector's own history up to t (expanding window, at least 24 monthly observations).
- **Relative momentum (MOM).** MOM(s,t) = P(s,t-1) / P(s,t-12) - 1, the return from twelve months ago to one month ago. Subtracting the benchmark's return over the same window would not change the ranking across sectors, so the raw return is used.

Given the three-sector universe, each signal is converted to a normalised cross-sectional rank between 0 and 1 among eligible sectors. This ranking reduces the influence of extreme raw values, including distorted Auto earnings in 2020–2021, but does not eliminate the limitations of a small cross-section. A sector is eligible when VAL and MOM are available. If EG is missing for a sector-month, the remaining signal weights are rescaled. Strategy A uses a composite score of 0.4 EG + 0.3 VAL + 0.3 MOM. Strategy B uses EG and VAL only, with weights rescaled; Strategy C uses MOM only. P/B is used for valuation rather than P/E because the P/E-derived earnings series contains the structural anomalies described above. Auto becomes eligible in June 2013; before that date, Strategy A selects from only two sectors and therefore coincides with Strategy E.

8. Backtesting design

Strategies. Strategy A selects the two highest-ranked sectors under the composite score and allocates equal weights to them. Strategy B uses the fundamental-only ranking, and Strategy C uses momentum alone. Strategy D is the Nifty 100 price-return index, the primary benchmark; the Nifty 100 TRI is a secondary benchmark. Strategy E holds all eligible sectors at equal weights and rebalances quarterly.

Timing and returns. Signals are calculated using information available at the final trading day of March, June, September and December. The resulting positions are held for the following three months, with portfolio weights allowed to drift between rebalances. Monthly sector returns are price returns. A secondary total-return approximation adds one-twelfth of the dividend yield to monthly sector returns and compares the resulting portfolios with the Nifty 100 TRI; this approximation is imperfect and should not be interpreted as a substitute for index total-return data.

Transaction costs. The primary specification applies a one-way cost of 25 basis points to traded portfolio value at each rebalance. This assumption was selected before the test-period run. Sensitivity analyses use 0, 50 and 100 basis points. Sector indices are not directly investable, so practical implementation would require funds or baskets that may introduce additional tracking error and costs.

Evaluation periods and code freeze. The development period runs from January 2011 to March 2018 (87 months) and was used to check the analysis pipeline. The test period runs from April 2018 to September 2026 (102 months). The backtest engine was frozen before the test slice was run (SHA-256 prefix: 075854c2e8875433), and the test slice was run once. However, because the framework was developed in 2026 with knowledge of historical data, this split is procedural rather than a fully independent, prospectively specified out-of-sample test.

Statistical methods. Sharpe ratios are calculated from monthly excess returns and annualised using the square root of 12. Differences in Sharpe ratios are evaluated using a circular block bootstrap with block length 6 and 10,000 resamples; block lengths of 3 and 12 are sensitivity checks. A Jobson–Korkie test with Memmel's correction is reported as a secondary check\references for Jobson and Korkie (1981) and Memmel (2003). These procedures are not identical to the Ledoit–Wolf (2008) method. Benchmark-regression alpha is estimated using Newey–West standard errors with three lags. Other reported statistics include CAGR, volatility, maximum drawdown, active return, tracking error, information ratio, turnover and the one-way cost at which active return falls to zero.



9. Results and statistical analysis

All results in this section are reported as outputs of the backtest code described in Appendix C. Unless otherwise stated, test-period statistics use 102 monthly observations from April 2018 through September 2026, sector price returns, the Nifty 100 price-return index as the benchmark and an assumed one-way transaction cost of 25 basis points.

9.1 Performance

Table 1. Test-period performance (April 2018 to September 2026).

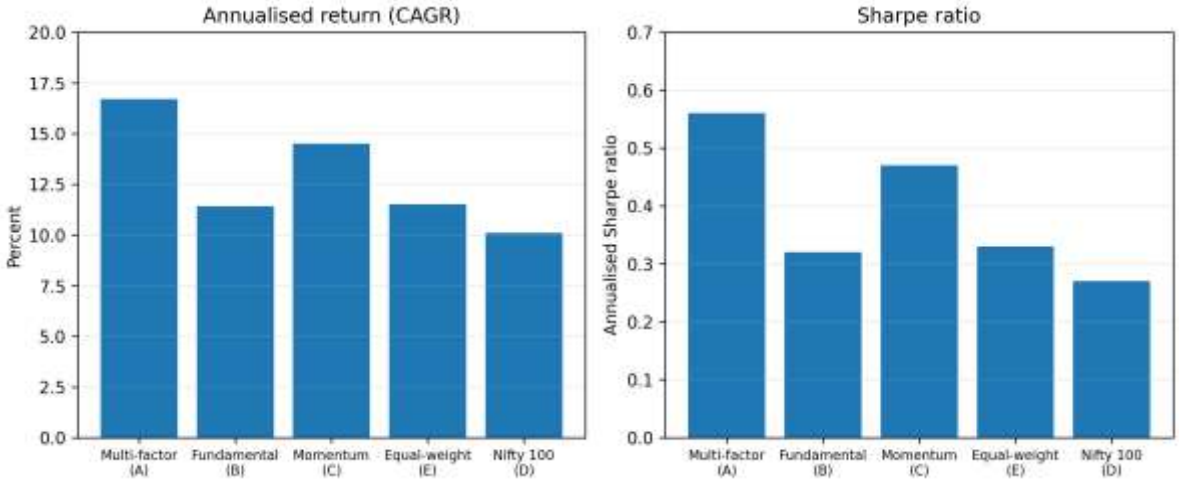


Figure 2. Test-period CAGR and Sharpe ratios by strategy (April 2018–September 2026).

Strategy	CAGR	Volatility	Sharpe ratio	Maximum drawdown	Active CAGR vs D	Tracking error	Information ratio
A: multi-factor rotation	16.7%	19.9%	0.56	-38.6%	+6.6%	8.5%	0.76
B: fundamental only	11.4%	19.8%	0.32	-39.5%	+1.3%	10.0%	0.17
C: momentum only	14.5%	19.1%	0.47	-29.6%	+4.4%	8.5%	0.50
E: equal-weight sectors	11.5%	19.0%	0.33	-36.6%	+1.4%	6.6%	0.24
D: Nifty 100 (price return)	10.1%	17.2%	0.27	-28.8%	n/a	n/a	n/a

Notes: Sharpe ratios use the debt-index risk-free proxy. Annual traded volume as a multiple of portfolio value: A 1.43, B 0.67, C 0.96, E 0.23.

Strategy A records the highest CAGR and Sharpe ratio among the tested strategies, but it also experiences a maximum drawdown of 38.6%, deeper than that of the benchmark and all strategies except B. Its volatility also exceeds the benchmark's. Over the same period, the individual Bank, IT and Auto indices returned approximately 10.0%, 9.8% and 11.0% annually, respectively, close to the benchmark's 10.1%. This comparison is consistent with the possibility that allocation timing contributed to Strategy A's result, although it does not by itself establish causality. Across 34 rebalances from March 2018 onward, Bank was selected 25 times, Auto 24 times and IT 19 times.

Table 2. Development-period diagnostics (January 2011 to March 2018, 87 months).

Strategy	CAGR	Volatility	Sharpe ratio
A	10.0%	17.2%	0.14
B	10.3%	17.2%	0.15

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Strategy	CAGR	Volatility	Sharpe ratio
C	7.4%	17.7%	0.00
E	10.7%	17.1%	0.18
D	7.9%	16.1%	0.02

During the development period, Strategy A did not outperform Strategy E, while the momentum-only strategy (C) recorded the weakest result. The ordering of strategies in the test period was therefore not replicated in the development period. On the approximate total-return basis (Appendix D), the test-period ordering is unchanged: Strategy A has a CAGR of 18.1% and a Sharpe ratio of 0.62, compared with 11.4% and 0.34 for the Nifty 100 TRI.

9.2 Statistical tests

Table 3. Sharpe-ratio differences, test period.

Comparison	Sharpe difference	95% interval	p (block 6)	p (block 3)	p (block 12)	p (Jobson-Korkie)
H1: A vs D	+0.28	-0.03 to +0.58	0.070	0.070	0.081	0.059
H2: A vs E	+0.23	-0.05 to +0.45	0.076	0.089	0.044	0.085
A vs B	+0.24	+0.04 to +0.51	0.041	0.048	0.033	0.107
A vs C	+0.09	-0.28 to +0.37	0.601	0.607	0.640	0.567

Notes: The reported bootstrap p-values are two-sided. Confidence intervals are percentile intervals from the block-length-6 bootstrap. For H3, the larger of the paired p-values for A versus B and A versus C is used (0.60).

The Holm-adjusted p-values for H1, H2 and H3 are 0.21, 0.21 and 0.60, respectively; none of the three primary null hypotheses is rejected at conventional significance levels. The bootstrap results indicate a difference between Strategy A and the fundamental-only strategy B, but not between A and the momentum-only strategy C. The unadjusted H2 p-value falls below 0.05 under block length 12, but this sensitivity result does not alter the conclusion after accounting for multiple testing.

A regression of Strategy A's monthly excess returns on benchmark excess returns produces an annualised alpha estimate of 6.2% (t = 1.98; Newey–West p = 0.048), a beta of 1.05 and an R-squared of 0.82. The corresponding regression for Strategy E produces an alpha estimate of 1.4% (p = 0.49). The alpha p-value is an unadjusted result from an exploratory analysis and is not treated as conclusive evidence of abnormal performance.

Economic relevance. Relative to benchmark D, Strategy A has a net active return of 6.6% per year, an information ratio of 0.76 and an estimated one-way cost break-even of approximately 433 basis points. Relative to Strategy E, the corresponding figures are 5.3%, 0.65 and approximately 348 basis points. The point estimates exceed the pre-specified economic thresholds, but the statistical evidence remains inconclusive.

Table 4. Strategy A under alternative one-way costs, test period.

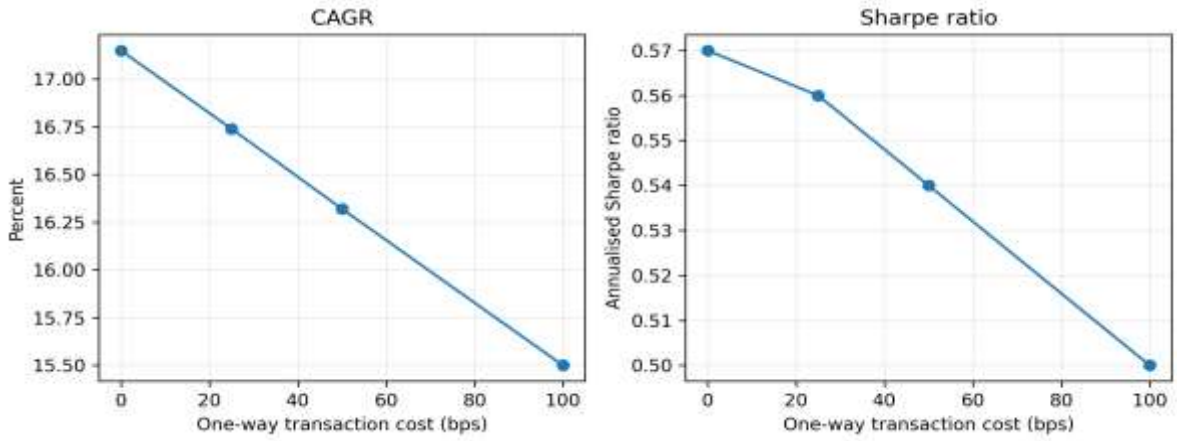


Figure 4. Sensitivity of Strategy A's CAGR and Sharpe ratio to assumed one-way transaction costs.



One-way cost	CAGR	Sharpe ratio	Active CAGR vs D
0 bps	17.15%	0.57	7.05%
25 bps	16.74%	0.56	6.64%
50 bps	16.32%	0.54	6.23%
100 bps	15.50%	0.50	5.41%

9.3 Robustness and concentration

Table 5. Variants of Strategy A, test period (sensitivity analysis only).

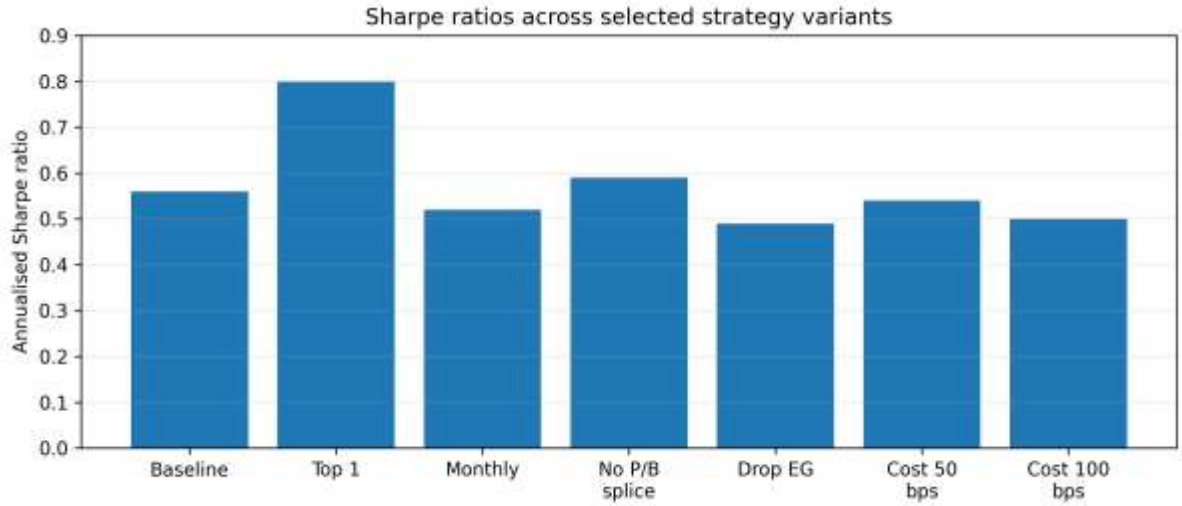


Figure 5. Sharpe ratios for selected robustness variants; variants are sensitivity analyses, not independently selected models.

Variant	Sharpe ratio	CAGR	Active CAGR vs D	Information ratio	Maximum drawdown
Baseline (top 2, quarterly, spliced, 25 bps)	0.56	16.7%	+6.6%	0.76	-38.6%
Top 1 sector	0.80	24.9%	+14.8%	0.91	-27.7%
Monthly rebalancing	0.52	15.8%	+5.7%	0.67	-39.6%
No P/B splice	0.59	17.6%	+7.5%	0.84	-38.6%
Minimum history 36 months	0.56	16.7%	+6.6%	0.76	-38.6%
Drop earnings growth (0/50/50)	0.49	15.1%	+5.0%	0.59	-32.5%
Cost 50 bps	0.54	16.3%	+6.2%	0.72	-38.8%
Cost 100 bps	0.50	15.5%	+5.4%	0.63	-39.2%

Across 36 combinations of factor weights (increments of 0.1, with each weight at least 0.1), the test-period Sharpe ratio ranges from 0.30 to 0.56. The baseline 40/30/30 specification attains the highest Sharpe ratio in this grid. Although those weights were specified before the grid analysis, the result remains sensitive to weighting choices and could reflect a favourable configuration by chance. The top-one-sector variant has a higher Sharpe ratio, but it was not the baseline specification and is reported only as a sensitivity analysis.

Table 6. Calendar-year returns, Strategy A versus the Nifty 100 (price return).

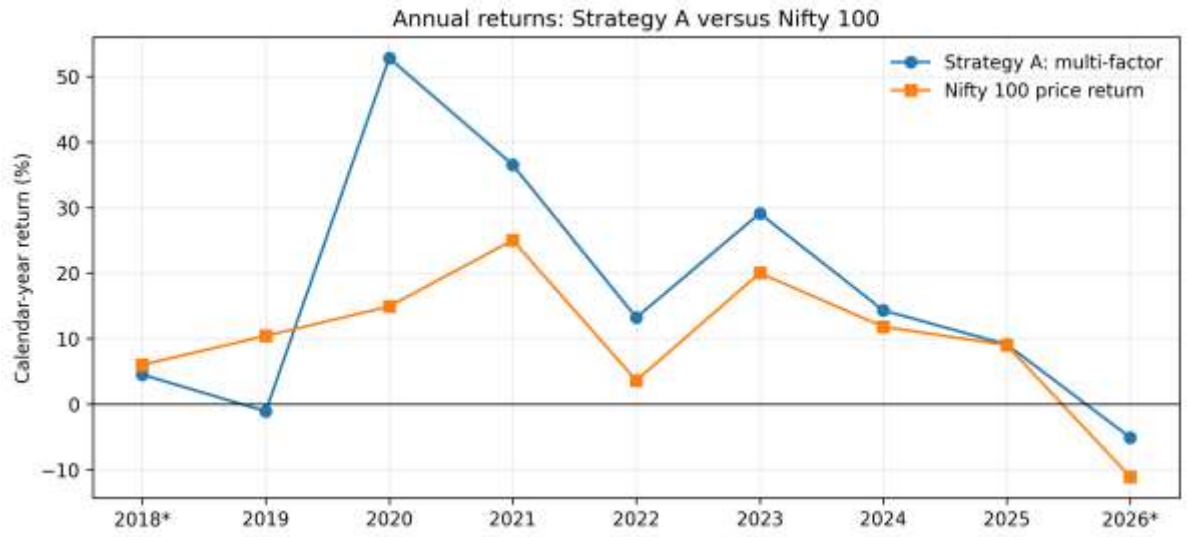


*Figure 3. Calendar-year returns for Strategy A and the Nifty 100; * denotes partial-year observations.*

Year	A	D
2018 (April to December)	4.5%	6.0%
2019	-1.1%	10.4%
2020	52.8%	14.9%
2021	36.5%	25.0%
2022	13.2%	3.6%
2023	29.1%	20.0%
2024	14.3%	11.8%
2025	9.1%	9.0%
2026 (January to September)	-5.1%	-11.1%

The largest return differences occur in 2020 and 2021; Strategy A underperforms the benchmark in 2018 and 2019.

10. Discussion

The point estimates favour the rotation strategy, but three findings limit the strength of the conclusions. First, the confidence intervals for Sharpe-ratio differences against both the market benchmark and the equal-weight portfolio include zero, and none of the primary hypotheses remains statistically significant after the multiple-testing adjustment. Second, Strategy A cannot be distinguished from the momentum-only rule. This is consistent with evidence that industry momentum can be an important component of return continuation (Moskowitz & Grinblatt, 1999), but it also means that this sample does not establish an incremental contribution from the earnings and valuation signals. Third, the fundamental-only rule performs similarly to the equal-weight sector portfolio, suggesting that the index-level earnings-growth and valuation measures used here may contain limited incremental information in this setting. The result is concentrated around 2020–2021, was not replicated in the development period and is sensitive to factor weights.

The benchmark comparison also requires caution. Strategy A holds two of the three available sectors and has an estimated beta of 1.05; some of its higher return may therefore reflect exposure to these sectors rather than successful selection. Strategy E provides a more direct comparison with passive ownership of the same sector universe, and the estimated performance gap between A and E is smaller than the gap between A and the broad-market benchmark. The estimated cost break-even levels suggest that assumed trading costs alone do not eliminate the point-estimate advantage, but they do not address tracking error, investability constraints or uncertainty in the return estimates.



11. Practical and managerial implications

For practitioners, this exercise illustrates how a judgement-based sector framework can be translated into explicit rules and evaluated systematically. The results highlight the importance of testing a strategy against both a broad market benchmark and a passive portfolio of the same assets, and of documenting the rules before evaluating the test period. In this sample, the concentrated rotation strategy experienced a maximum drawdown of approximately 39%, compared with approximately 29% for the benchmark. The analysis is not investment advice and does not justify deploying the strategy without further testing across a broader sector universe and with investable instruments.

12. Limitations and future research

- **Universe.** Three sectors, chosen by data availability, limit generalisation and power; rotation among three assets is a weak test. Adding sectors (for example FMCG, Pharma, Metals, Energy) is the most useful extension, and valuation data for FMCG were not available.
- **Statistical power and period.** About 8.5 years of monthly data cannot detect modest Sharpe-ratio differences. The result is concentrated around 2020-21, and the framework was formed with knowledge of history.
- **Data issues.** NSE valuation series contain methodology breaks (Section 6) that were adjusted or excluded by rule; the P/B adjustment includes a normal annual update and is approximate. Yahoo prices for two sectors were not cross-checked against NSE data. The total-return basis is approximated. The risk-free proxy carries credit risk.
- **Methods.** The Sharpe-difference tests approximate the Ledoit-Wolf procedure. Sectors are measured with index-level P/E and P/B, not company fundamentals, so earnings growth is a coarse signal. Index returns are not directly investable.
- **Scope.** Stock selection and news sentiment, the other two lenses of the practitioner framework, are not tested. Future work with point-in-time stock-level data (for example CMIE Prowess) could test the full framework and use a larger sample.

13. Conclusion

Across the test period, a rule-based strategy rotating among three NSE sector indices produced higher estimated returns and a higher Sharpe ratio than the Nifty 100 and an equal-weight portfolio of the same sectors, after assumed transaction costs. However, these differences were not statistically significant after adjustment for multiple testing, the relative performance was not replicated in the development period, results depended on factor weights and gains were concentrated around 2020–2021. The findings should therefore be treated as exploratory evidence that motivates further testing, not as evidence of persistent sector-rotation outperformance.

Declarations

- Author contributions, affiliations and authorship: [AUTHOR ACTION: Complete author names, affiliations, contribution statements and corresponding-author details in accordance with institutional and journal requirements.]
- Permissions and confidentiality: Institutional approval and clearance from the firm were obtained, as confirmed by the author. No client information or proprietary templates are reproduced.]
- Data and code availability: The analysis uses index data obtained from NSE Indices and Yahoo Finance, subject to their respective terms of use. The backtest code and derived monthly workbook are available on request.
- Relation to the OJT report: This study is based in part on work undertaken for the author’s on-the-job training report submitted as part of a degree programme.



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Holm (1979), Jobson and Korkie (1981), Memmel (2003) and Newey and West (1987);

Appendix A. Data audit summary

Series	Coverage	Result
Nifty 100 price return	2 Jan 2008 to 30 Sep 2026	4,643 days, no gaps over 7 days
Nifty 100 TRI	1 Jan 2009 to 30 Sep 2026	4,398 days; TRI minus price return about 1.24% a year
Nifty 100, Bank, IT valuation	1 Jan 2009 to 30 Sep 2026	4,398 days each; Bank has 42 blank dividend-yield days
Nifty Auto valuation	12 Jul 2011 to 30 Sep 2026	3,772 days
Nifty Auto price	1 Jan 2009 to 30 Sep 2026	4,398 days
Bank and IT price (Yahoo)	2008 to 30 Sep 2026	29 NSE trading days missing from 2009; forward-filled up to 3 days
Risk-free proxy	1 Jan 2009 to 30 Sep 2026	Calendar-day series, about 7.4% a year on average



Appendix B. Structural breaks in NSE valuation series

Date	Series	Observation	Treatment
29 Sep 2023	P/B, all four	Implied book value up 25% (Nifty 100), 19% (IT), 24% (Auto), 4.5% (Bank)	Spliced; unadjusted variant run
31 Mar 2021	P/E, all four	Implied earnings jump of about 15% (Nifty 100, IT), 19% (Bank), fall of 73% (Auto)	Growth windows spanning the date set to missing
25 Sep 2019	P/E, Bank	Implied earnings up 70% in a day; Nifty 100 up 9%	Windows spanning the date set to missing for Bank

Appendix C. Reproducibility

The files backtest.py and run_all.py reproduce all results from the Data Master workbook (Monthly and Daily_Data sheets). The engine hash is the SHA-256 prefix 075854c2e8875433. Random seed for bootstrap: 20261023. Results are written to the Backtest Results workbook.

Appendix D. Approximate total-return basis, test period

Strategy	CAGR	Sharpe ratio
A	18.1%	0.62
B	12.7%	0.38
C	15.9%	0.54
E	12.9%	0.40
D (Nifty 100 TRI)	11.4%	0.34

Sector total return approximated as price return plus dividend yield divided by twelve.