JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

A VALIDATION-GATED, VALUE-RANKED AND INVERSE-VOLATILITY WEIGHTED EQUITY ALLOCATION FRAMEWORK: A POINT-IN-TIME BACKTEST ON THE NIFTY 500 UNIVERSE

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Abstract : This study describes a deterministic, rules-based framework for allocating capital to Indian equities and reports a point-in-time backtest on the NIFTY 500 universe. Four candidate factors (Value, Quality, Momentum and change in institutional ownership) are ranked within sectors, and each must pass a predictive validation test before it can enter the composite score. Only Value passed (mean information coefficient 0.070 over 45 months), so the model tested here is in effect a single-factor value strategy; because historical margin-of-safety data were not available, Value was measured in the test by earnings, free-cash-flow and book yields alone. Selected stocks are weighted by the inverse of their 60-day volatility, subject to single-stock caps of 7–8% and a 25% sector cap, and are rebalanced quarterly after transaction charges, slippage and Indian capital gains tax. Three risk profiles differ in universe breadth and number of holdings. Stock price history in the study database begins in late 2021, so although the simulation is configured from 3 March 2020, the first portfolio could only be formed on 2 December 2022; the evaluation therefore covers 2 December 2022 to 16 November 2026 (16 quarterly rebalances, about four years). Over that period the Medium profile returned 25.31% a year after tax (28.25% before tax) against 10.57% for the NIFTY 500 price index, with a deeper maximum drawdown (−22.33% against −18.84%) and a higher Sharpe ratio (1.10 against 0.39). The results vary materially with the choice of rebalance months and are subject to clear limitations: a short sample, factor selection over the same period as the backtest, missing price history for 183 of the 681 stocks that were index members during the period, annual-only fundamental data, and the exclusion of dividends from both strategy and benchmark. The findings are therefore presented as a transparent case study rather than as evidence of a persistent return premium.

IndexTerms - Value Investing, Factor Validation, Inverse-Volatility Weighting, Capital Allocation, NIFTY 500, Point-in-Time Backtesting, Transaction Costs, Capital Gains Tax.

I. INTRODUCTION

Retail investors in India increasingly use stock screeners that filter companies on valuation and quality metrics. Most such tools stop at producing a list of names. They rarely say how much capital each stock should receive, how often the list should be refreshed, what trading costs and taxes do to returns, or whether the screening rules actually predicted returns in the past. A screen that looks attractive on today's data can also hide two well-known backtest errors: look-ahead bias, where information is used before it was public, and survivorship bias, where only companies that survived to the present are tested.

This paper describes the allocation engine built into SBScreener, a stock research platform developed by the author, and tests it on the NIFTY 500 universe. The framework has three features that are central to the study:

• A validation gate: each candidate factor is tested for predictive power on its own, and only factors that pass are used. Factors that fail are reported, not hidden.

• Explicit position sizing: selected stocks are weighted by inverse volatility with stock and sector caps, so the output is a full set of portfolio weights rather than a list.

• Realistic accounting: the backtest uses point-in-time data access, executes trades on the day after each signal, and deducts transaction charges, slippage and Indian short- and long-term capital gains tax.

The contribution is a transparent, reproducible description of such a system and an honest report of its simulated behaviour, including the factors that failed, the sensitivity of the results, and the data limitations that remain.

II. LITERATURE REVIEW

Modern portfolio theory (Markowitz, 1952) established mean-variance optimisation as the basis of portfolio construction, but its sensitivity to estimated expected returns makes it unstable in practice (Michaud, 1989; Fabozzi et al., 2002). Factor models offer an

alternative view of the cross-section of returns. The arbitrage pricing theory of Ross (1976) and the work of Fama and French (1992, 1993) showed that characteristics beyond market beta, notably size and value, help explain average returns. Subsequent research documented a value premium (Basu, 1977; Lakonishok et al., 1994), cross-sectional momentum (Jegadeesh and Titman, 1993; Carhart, 1997) and profitability or quality effects (Novy-Marx, 2013; Asness et al., 2019).

A separate strand of work found that low-volatility stocks have historically delivered better risk-adjusted returns than the capital asset pricing model predicts (Haugen and Heins, 1975; Blitz and van Vliet, 2007; Frazzini and Pedersen, 2014). On portfolio construction, risk parity approaches allocate so that each holding contributes equally to portfolio risk (Qian, 2005; Maillard et al., 2010; Roncalli, 2013). Inverse-volatility weighting, used in this study, is a simpler special case: it equalises risk contributions only when all pairwise correlations are equal, so it is described here as volatility weighting rather than risk parity.

Backtests of such strategies in Indian equities face practical difficulties. Index constituent histories are not distributed in a ready-to-use form, fundamental data are often stored with revised rather than as-reported values, and many studies ignore securities transaction tax, stamp duty, slippage and capital gains tax. This study addresses these issues as far as the available data allow and reports where they remain unresolved.

III. FRAMEWORK

The framework is deterministic: the same inputs always produce the same portfolio. It contains no machine-learning components and no parameters that adjust themselves automatically.

A. Universe and eligibility

At each rebalance date t, the investable universe U_t is the set of stocks that were members of the NIFTY 500 index on that date, taken from a point-in-time membership file (Section IV). A stock is eligible only if its median daily traded value over the previous 63 trading days is at least ₹5 crore, its price is at least ₹20, it has at least 252 trading days of price history, at least three of the four factors can be computed for it, and it carries no forensic flag (negative operating cash flow combined with rising debt). A new purchase additionally requires the stock to trade above its 200-day exponential moving average; stocks already held are not sold for failing this condition. The moving-average condition is a yes/no filter and is not part of the score.

B. Factor scoring

Four candidate factors are computed from data that were publicly available on date t. Value is designed as the average of two ranks: a margin-of-safety measure relative to estimated intrinsic value, and a yield measure. For most sectors the yield measure is the average of earnings yield and free-cash-flow yield; for banks and other financial companies, where free cash flow is not meaningful, it is the average of earnings yield and book-to-price. Margin of safety has only been recorded since the platform began storing it daily and was not available for any stock at the start of the test, so in the backtest Value was in effect measured by the yield component alone. Quality uses a composite of profitability, balance-sheet strength and earnings stability. Momentum uses 12-month and 6-month price returns, each excluding the most recent month. Institutional is the quarter-on-quarter change in the combined holding of domestic and foreign institutions.

Raw values X_{i,f} for stock i and factor f are winsorised at the 2.5th and 97.5th percentiles and converted to a percentile rank within the stock's sector (or within the whole universe when the sector has fewer than eight eligible stocks):

$$R_{i,f} = 100 \times rank_sector(X_{i,f}) / n_sector \quad (1)$$

The composite score is the equal-weighted average of the ranks of the factors in the validated set F*:

$$S_i = (1 / |F^*|) \times \Sigma_{f \in F^*} R_{i,f} \quad (2)$$

C. Validation gate

Before a factor can enter F*, it is tested on its own. At each month-end with at least 20 eligible stocks, the Spearman rank correlation (information coefficient, IC) is computed between the factor rank and each stock's subsequent three-month (63 trading day) return minus the average return of its sector; months with fewer than 10 usable pairs are skipped. A factor passes only if its mean IC is at least 0.02, the IC is positive in at least 55% of months, and average forward returns rise from the lowest-ranked to the highest-ranked group (a monotonicity score of at least 0.6, with the top group beating the bottom group). A factor with fewer than 36 usable months is classed as having insufficient history. The test was run over month-ends from 30 November 2022 to 31 July 2026. Table 1 shows the outcome.

Table 1: Factor validation outcome (30 November 2022 to 31 July 2026)

Factor	Months	Mean IC	IC positive	Result	Weight
Value	45	0.070	67%	Pass	100%
Momentum	45	0.009	58%	Fail	0%
Institutional ownership change	45	−0.009	44%	Fail	0%
Quality	0	–	–	Insufficient history	0%

Source: model Methods Report, model version 2026.11-v1, configuration hash eb98195d. Weight is the share of the composite score in all three profiles.

Momentum had a positive IC in more than half of the months but its average was below the 0.02 threshold. Because only Value passed, S_i reduces to the Value rank, and the tested model is a single-factor value strategy. The validation period overlaps almost entirely with the backtest period, so the choice of factor is not independent of the results (Section VII).

D. Selection and weighting

The N eligible stocks with the highest scores are selected, where N depends on the risk profile (Table 2). To limit turnover, an existing holding is kept as long as its rank remains within the top 2N. Each selected stock receives a raw weight proportional to the inverse of its recent volatility σ_i, measured as the standard deviation of daily returns over the previous 60 trading days (a separate screen based on 252-day volatility is also applied when forming the eligible set):

$$w_i^{raw} = (1/\sigma_i) / \Sigma_{j=1..N} (1/\sigma_j) \quad (3)$$

The raw weights are then constrained by a single-stock cap C_stock, a sector cap C_sector and a minimum weight of 2%, with excess weight redistributed to unconstrained holdings until all limits hold:

$$w_i \le C_stock, \quad \Sigma_{i \in sector\ k} w_i \le C_sector \quad (4)$$

Positions whose weight has drifted less than 1.5 percentage points from target are not traded at a rebalance.

E. Exits between rebalances

Between rebalances, a holding is sold only if a forensic flag appears or if its weekly closing price falls 30% or more below its entry price. There are no tight stop-losses, because frequent stops in a portfolio held for quarters tend to sell on ordinary volatility and increase short-term tax.

F. Market regime overlay

The framework includes an optional overlay that reduces equity exposure to 80% or 60% when market breadth (the share of the universe trading above its 200-day moving average) falls through set thresholds, with separate entry and exit levels to avoid frequent switching. The overlay is kept only if it reduces maximum drawdown by at least 5 percentage points at a cost of no more than 1.5 percentage points of annual return. It did not meet this test (Section VI) and is switched off in the reported model. When active, the non-equity portion is simulated as cash only.

G. Risk profiles

Three profiles apply the same rules to universes of different breadth. Table 2 lists the settings used in the backtest.

Table 2: Risk profile settings

Setting	Low	Medium	Aggressive
Universe (largest stocks by market capitalisation)	Top 100	Top 250	All 500
Number of holdings	15	20	25
Maximum weight per stock	8%	8%	7%
Maximum weight per sector	25%	25%	25%

The profile names describe the intended investor rather than a measured outcome. As Section V shows, the Low profile had lower volatility but not a smaller drawdown than the other two.

IV. DATA AND METHODOLOGY

A. Simulation window and rebalancing

The simulation runs from 3 March 2020 to 16 November 2026, covering 1,664 trading days. Rebalancing is quarterly in March, June, September and December, giving 27 rebalances; the last was executed on 2 September 2026. Signals are computed on the trading day before each rebalance and trades execute on the following trading day, so no trade uses information from its own execution day.

Stock price history in the study database begins in late 2021. At the first seven rebalances (March 2020 to September 2021) no index member had stored prices, and at the next four (December 2021 to September 2022) every stock failed the 252-day history requirement. The model therefore held only cash until the first portfolio was formed on 2 December 2022. This cash period reflects missing data, not a decision by the model, and it is excluded from the evaluation. The results cover 2 December 2022 to 16 November 2026, which contains 16 rebalances with holdings.

B. Point-in-time data

All historical inputs are read through a single access layer that returns only records available on the calculation date. The study uses annual financial statements only (3,538 company-year records from 2016 onwards); quarterly results are not used. Because announcement dates are not stored, each annual result is treated as available from 60 days after the financial-year end of 31 March, that is, from about 30 May, which is the regulatory deadline for listed companies to publish audited annual results. Shareholding data are used from their filing date where stored, and otherwise from 30 days after the quarter end.

Index membership is taken from a file of 935 entry and exit records covering 824 distinct symbols, compiled from NIFTY Indices reconstitution announcements since November 2018. The file is known to contain a small number of unresolved gaps. More importantly, 183 of the 681 stocks that were index members at some point during the evaluation period (about 27%), almost all of them companies that have since left the index, have no price history in the study database and could never be selected. Survivorship bias is therefore reduced but not removed, and the reported returns may be overstated.

C. Prices and benchmark

Stock prices are adjusted for splits and bonus issues but not for dividends. The benchmark is the NIFTY 500 price return index, which also excludes dividends, and benchmark statistics are always computed over exactly the same dates as the strategy they are compared with. Excluding dividends on both sides keeps the comparison consistent; it understates the absolute return of both series, and a value-tilted portfolio may hold higher-yielding stocks than the index.

D. Costs and tax

Each trade is charged 0.12% per side for brokerage, securities transaction tax, stamp duty and exchange fees, plus slippage of 0.25% per side for the 100 largest stocks and 0.50% for the rest. Capital gains tax is computed on a first-in, first-out lot basis and charged at each financial year end (31 March): short-term gains at 20% and long-term gains (holding period over 365 days) at 12.5% above an annual exemption of ₹1,25,000, with short-term losses offset against long-term gains. Uninvested cash earns 6% a year, compounded daily, and the same 6% is used as the risk-free rate in Sharpe ratios.

V. RESULTS

A. Evaluation period

Table 3 reports performance from the first portfolio formation on 2 December 2022 to 16 November 2026.

Table 3: Performance, 2 December 2022 to 16 November 2026

Metric	Low	Medium	Aggressive	NIFTY 500 (price)
Annual return, pre-tax	20.82%	28.25%	29.47%	10.57%
Annual return, post-tax	18.61%	25.31%	26.20%	–
Annual volatility	14.51%	16.85%	17.26%	13.54%
Maximum drawdown	−25.52%	−22.33%	−22.16%	−18.84%
Sharpe ratio (rf = 6%)	0.87	1.10	1.12	0.39
Calmar ratio, pre-tax	0.84	1.41	1.38	0.56
Calmar ratio, post-tax	0.73	1.13	1.18	–
Longest period below a previous peak (days)	777	407	386	780

Benchmark figures are before any tax, as an index has no tax liability; compare them with the pre-tax rows. All series exclude dividends.

All three profiles returned more than the benchmark over this period, by roughly 10 to 19 percentage points a year before tax. This higher return came with higher risk: each profile was more volatile than the index and had a deeper maximum drawdown. The Medium and Aggressive profiles recovered from their worst declines faster than the index, which spent 780 days below its previous peak. The Low profile, restricted to the 100 largest stocks, had the lowest return of the three and the deepest drawdown, so its name should not be read as a guarantee of smaller losses.

Average turnover per rebalance after the first purchase was about 15% for Low, 19% for Medium and 17% for Aggressive. Because the period covers only about four years and a single market environment, in which value-oriented Indian stocks performed strongly, these figures should not be extrapolated.

Statistics for the whole configured window from March 2020 are not reported as a model result. Because the first 11 rebalances held cash only for lack of price data, those figures would mainly measure the cash return during the March 2020 market decline rather than the strategy.

VI. ROBUSTNESS

Table 4 reports how the Medium profile responds when one setting is changed at a time. Figures are post-tax and, as produced by the robustness module, cover the full configured window from March 2020, including the cash-only months at 6%. Their absolute levels are therefore lower than in Table 3 and should be compared only with each other.

Table 4: Medium profile sensitivity (post-tax, configured window 3 March 2020 to 16 November 2026)

Variation	Setting	Annual return	Volatility	Max drawdown	Sharpe
Baseline	As reported	16.87%	12.95%	−22.33%	0.84
Number of holdings	15	18.11%	13.71%	−22.05%	0.88
Number of holdings	30	15.67%	12.15%	−21.06%	0.80
Rebalance months	Jan/Apr/Jul/Oct	13.59%	12.49%	−23.91%	0.63
Rebalance months	Feb/May/Aug/Nov	15.29%	11.88%	−24.31%	0.79
Costs	Doubled	16.43%	13.02%	−22.85%	0.81
30% exit rule	Off	15.96%	13.01%	−22.13%	0.77
Regime overlay	On	15.49%	12.13%	−21.47%	0.79

Three observations follow. First, the result is sensitive to the choice of rebalance months: moving the schedule by one or two months lowered the Medium profile's annual return by 1.6 to 3.3 percentage points, and the reported March/June/September/December schedule was the best of the three tested for both the Medium and Aggressive profiles. Part of the reported return may therefore reflect timing rather than the factor itself. Second, doubling all costs reduced the annual return by only about 0.4 percentage points, so the result is not driven by optimistic cost assumptions. Third, the regime overlay reduced the maximum drawdown by less than one percentage point while lowering the annual return by about 1.4 percentage points; it fails the keep-or-kill test in Section III.F and is therefore switched off. The overlay had a similar effect on the Low and Aggressive profiles.

VII. LIMITATIONS

• Short sample. The evaluation period covers about four years and 16 rebalances in a single market environment. This is too short to establish whether the value effect observed is persistent, and no test of statistical significance is reported.

• Factor selection on the same data. Value was retained, and three other factors were discarded, using a validation test run from November 2022 to July 2026, almost the same period as the backtest. This favours the reported results.

• Value measured by yields only. The margin-of-safety half of the Value factor was not available historically, so the factor tested is narrower than the one the framework specifies.

• Annual fundamentals only. Financial data are annual and are used from about 30 May each year, so the yields used for selection can be up to a year out of date.

• Incomplete price coverage. 183 of the 681 stocks that were index members during the evaluation period, almost all of them companies that later left the index, have no price history and could not be selected. Returns may be overstated.

• Dividends excluded. Both strategy and benchmark exclude dividends. A total-return comparison is left for future work.

• Sensitivity to rebalance timing. Results changed materially with the choice of rebalance months.

• Simulation only. Results are hypothetical, do not reflect actual trading, and do not include market impact beyond the slippage assumptions.

VIII. CONCLUSION

This paper described a deterministic equity allocation framework that ranks stocks within sectors, admits a factor only after a predictive validation test, weights holdings by inverse volatility within stock and sector caps, and accounts for Indian trading costs and capital gains tax. On the available NIFTY 500 data, only the Value factor passed validation, so the tested model is a single-factor value strategy.

Over the evaluation period from December 2022 to November 2026, the strategy earned substantially more than the NIFTY 500 price index but with higher volatility and a deeper maximum drawdown. Given the short sample, the in-sample factor selection, the narrower yield-only Value measure, the sensitivity to rebalance timing and the incomplete price coverage, the results should be read as a description of how the framework behaved rather than as evidence of a reliable premium.

Future work will load price history from 2018 so that the full constituent history can be tested, add the missing prices for former index members, record announcement dates and quarterly results, include the margin-of-safety measure once enough history exists, re-run the validation of Quality once 36 months of data exist, compare against the NIFTY 500 total return index, and report the monthly live track record of the model, which is recorded without later revision.

DECLARATIONS

Competing interests: The author developed and owns SBScreener, a commercial subscription platform that implements this model. The author is a Director of Fintegro Technologies Pvt Ltd and is employed by Fractal Analytics; neither organisation had any role in this work.

Funding: This research received no external funding.

Data availability: Index price data were obtained from the NIFTY Indices historical data service; constituent histories were compiled from NIFTY Indices reconstitution announcements; stock prices and fundamentals were drawn from public market data. The model configuration, rebalance log and derived results are available from the author on reasonable request, subject to source licence terms.

Use of AI tools: AI-assisted tools were used for language editing and drafting. The model design, rules, data validation and all reported results are the author's own, in line with COPE guidance.

Disclaimer: This paper reports research on a simulated model. It is not investment advice or a recommendation to buy or sell any security.

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