Performance Analysis of a Deletions – Based investment strategy in the Indian Equity Market

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This study examines the performance and practicality of a deletions-based equities investment strategy in the Indian stock market, using models from developed markets. We create annual portfolios of Nifty 500 equities taken out over the past five years using a proprietary approach. To eliminate high-risk enterprises, a rigorous quality screening system uses six financial metrics: debt coverage, equity issuance, debt issuance, leverage change, and payout ratios. The worst 20% of stocks are eliminated from the investable universe each year using a percentile-based composite grading algorithm. Rebalanced annually on the last trading day of May, the portfolios typically contain 100 equally-weighted equities.

We adjust for survivorship bias, transaction costs, and liquidity constraints in our 14-year empirical research from 2010 to 2024 with over 1,000 stock occurrences.

When vetted for financial quality, index-excluded stocks offer considerable mean-reversion chances in Indian equities. The study shows that alternative indexing strategies outside factor models can impact ETF product design, institutional asset allocation, and smart beta developments in emerging markets. To improve the technique, future study might use dynamic weighting, sector-neutral positioning, and multi-factor overlays.

INTRODUCTION

Over the past two decades, the rise of smart beta and alternative index construction strategies has reshaped the investment management landscape. Moving beyond traditional market capitalization-weighted approaches, smart beta strategies seek to systematically capture specific factors such as value, momentum, quality, or volatility in an attempt to achieve superior risk-adjusted returns. Among these alternative strategies, those built around corporate events — including index additions and deletions — have received increasing academic and practitioner attention.

A deletions-based strategy focuses on stocks removed from major indices under the premise that such deletions may create temporary mispricing. According to the theory of mean reversion, securities that experience forced selling pressure due to index reconstitution may subsequently recover once temporary distortions subside, provided their underlying fundamentals remain intact. This phenomenon has been observed in several developed markets and offers an intriguing basis for systematic investment strategies.

The motivation for applying a deletions-based approach to the Indian market lies in its unique market structure, growing institutional participation, and the increasing importance of passive investment vehicles tied to major indices like the Nifty 500. Given these dynamics, studying how index deletions behave in India can offer valuable insights into market efficiency, price discovery mechanisms, and the potential for mean-reversion-based strategies in an emerging market context.

The primary objective of this research is to design, implement, and evaluate a systematic deletions-based investment strategy using the Nifty 500 universe, incorporating a quality screening framework to mitigate financial distress risks. By analyzing a comprehensive historical dataset from 2007 to 2024, this study aims to assess whether such a strategy can be effectively applied in the Indian equity market and to identify the challenges and opportunities associated with its implementation.

3. DATA & METHODOLOGY

3.1 DATA SOURCES

The study relies on a comprehensive dataset comprising stock price histories, fundamental financial ratios, and index constituent changes over an extended period from 2007 to 2024.

Historical daily adjusted closing prices for Indian equities were collected using the yfinance Python library, which offers a reliable interface for accessing publicly available market data. The dataset ensures coverage of all companies that were, at any point, part of the Nifty 500 universe or subsequently removed from it during the sample period.

Financial data was extracted by programmatically scraping Screener.in, a widely used platform for accessing fundamental data on Indian listed companies. Screener.in aggregates company financials from official filings and standardizes them across time periods, making it a suitable source for structured data extraction.

After retrieval, key financial ratios required for the strategy were computed manually using Python to maintain control over the formula definitions and ensure uniformity across all years and companies. This step also allowed for customization of ratio components in accordance with the specific requirements of the strategy. Key financial fields used in the calculations included income, total debt, equity issuance, retained earnings, gross profits, dividends, buybacks, and long-term assets and liabilities.

To track index constituent changes, data regarding annual additions and deletions from the Nifty 500 was sourced from official announcements made by the National Stock Exchange (NSE) and cross-referenced against third-party public repositories where necessary. All deletions between 2009 and 2024 were tracked to build an accurate and continuous deletion history, enabling the construction of a five-year trailing eligibility pool at every rebalance point.

It is acknowledged that despite efforts to ensure completeness, survivorship bias may exist due to the unavailability of complete historical financial data for companies whose trading was permanently halted or whose financial disclosures ceased to be available after delisting.

3.2 PORTFOLIO CONSTRUCTION

The portfolio construction methodology employed in this study was designed to systematically identify, screen, and invest in stocks removed from the Nifty 500 index, with the aim of capturing potential mean-reversion opportunities while minimizing exposure to financially distressed firms. The construction process was executed through a series of well-defined, rule-based steps as outlined below:

FIVE-YEAR DELETION LOOKBACK

At each annual rebalance date, a five-year lookback window was applied to identify all companies that had been removed from the Nifty 500 index during the preceding five calendar years. This step ensured that the investment universe was not limited to stocks recently deleted but included companies that may have experienced prolonged underperformance yet retained recovery potential. For instance, at the March 2020 rebalance, the eligible deletion pool included all companies dropped from the index between 2015 and 2019.

This five-year horizon was selected to strike a balance between capturing a wide enough sample of potential candidates and avoiding stocks that may have become fundamentally unviable due to extended declines.

QUALITY SCREENING USING FINANCIAL RATIOS

To evaluate the financial soundness of the deletion candidates, a quality screen was applied using six carefully chosen financial ratios:

Debt Coverage Ratio – measures the company's ability to meet debt obligations using operating income.

Equity Issuance Growth – assesses the dilution risk by evaluating the annual increase in outstanding shares.

Debt Issuance Growth – identifies increased reliance on debt financing.

Change in Leverage – captures shifts in long-term debt relative to total assets.

Total Payout Ratio – computed as five-year cumulative retained earnings to gross profits.

Net Payout Ratio – five-year average of dividends and buybacks relative to total assets.

These ratios collectively represent multiple dimensions of a firm's financial position, including solvency, capital structure, shareholder orientation, and earnings quality.

Each ratio was normalized using percentile ranking within the eligible universe for that year. This method assigned each company a score between 0 and 100 on each metric, reducing the influence of extreme outliers and enabling fair comparison across firms and years.

Metric	Description
Debt Coverage Ratio	Income relative to total debt obligations
Equity Issuance Growth	Year-on-year % growth in outstanding shares
Debt Issuance Growth	Year-on-year % growth in total debt
Change in Leverage	YoY change in Long-term Debt ÷ Total Assets
Total Payout Ratio	5-year Retained Earnings ÷ Gross Profits
Net Payout Ratio	5-year Dividends & Buybacks ÷ Total Assets

EXCLUSION OF THE BOTTOM 20%

Following the computation of a composite quality score obtained as the arithmetic mean of the six normalized scores all companies falling in the **bottom 20%** of the distribution were excluded. This step was intended to systematically eliminate firms showing the most severe signs of financial deterioration, such as excessive leverage, poor earnings retention, or aggressive equity issuance.

By excluding the lowest quintile, the strategy aimed to avoid allocating capital to companies with the highest risk of continued decline or default.

EQUAL-WEIGHT PORTFOLIO SELECTION

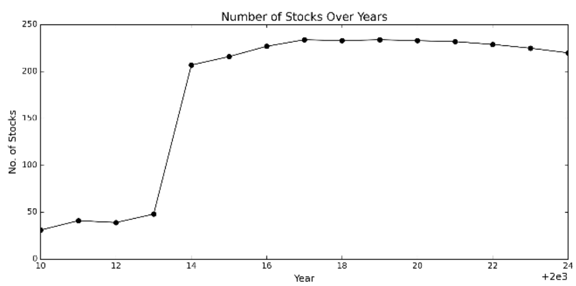
From the remaining pool of screened companies, the **top 100 stocks** were selected based on their quality score ranking. Each of these stocks was assigned an **equal weight,** regardless of market capitalization, sector, or historical performance. This choice reflects a belief in diversifying idiosyncratic risk while ensuring that no single position disproportionately drives overall performance.

The equal-weighting approach also avoids unintended tilts toward large-cap or high-volatility stocks and ensures that all constituents contribute equally to returns and risk.

ANNUAL REBALANCING IN MARCH

The portfolio was rebalanced annually on **March 31st**. On this date, the full process of deletion screening, quality scoring, and portfolio reconstruction was repeated using the most recent available data. All positions were liquidated and reallocated in accordance with the newly selected basket of equally weighted stocks.

This rebalancing frequency was chosen to limit trading costs while allowing sufficient time for mean-reversion effects to materialize and for updated financial data to be reflected in the screening process.



3.3 SCORING MECHANISM

The scoring framework for evaluating the financial health of companies in the deletions pool was designed to convert a diverse set of raw financial metrics into a standardized, comparable form. This was necessary to enable consistent ranking and filtering of firms across multiple dimensions of financial quality.

NORMALIZATION USING PERCENTILE RANKING

Given the varying scales, units, and distributions of the six financial ratios used in the quality screen, raw values were not directly comparable. To address this, **percentile ranking** was employed as the primary normalization method. Under this approach, each firm was assigned a score from 0 to 100 for each ratio based on its relative position in the annual distribution of the eligible pool.

Percentile ranking offers several key advantages:

- **Robustness to Outliers**: Extreme values do not disproportionately influence the scale, unlike z-scores.
- **Comparability Across Metrics**: All six metrics are transformed onto the same 0–100 scale, facilitating equal treatment during aggregation.
- **Interpretability**: Percentile scores are easy to understand and interpret in terms of relative ranking.

Z-score normalization was considered as an alternative but was ultimately not used due to its sensitivity to outliers and its assumption of normally distributed data, which did not hold for several financial metrics with skewed distributions.

CALCULATION OF COMPOSITE QUALITY SCORE

For each company, a **composite quality score** was computed as the **simple arithmetic average** of its six normalized percentile scores. Each financial metric was assigned an **equal weight of 16.67%**, reflecting the assumption that no single metric should dominate the overall quality assessment.

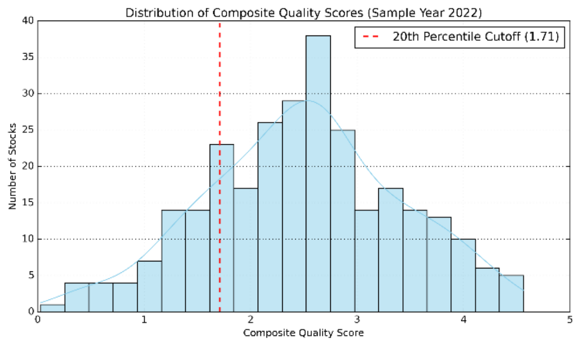
This composite score provided a unified measure of a firm's financial strength, capturing its standing across multiple dimensions including debt management, capital structure, payout discipline, and dilution risk.

The equal-weighted scoring methodology also helped maintain transparency and avoided overfitting or data mining, which could occur if subjective or optimized weights were used.

THRESHOLD-BASED FILTERING

After calculating the composite scores, a threshold filter was applied: **companies falling in the bottom 20%** of the score distribution were excluded from portfolio eligibility. This exclusion was applied annually, and only companies in the **top 80%** by quality score were retained for portfolio inclusion.

All remaining stocks that passed this quality screen were included in the final portfolio on an **equal-weighted** basis, regardless of how many companies met the criteria in a given year. This dynamic sizing allowed the portfolio to adapt to variations in market conditions and the financial health of the deletions pool each year.

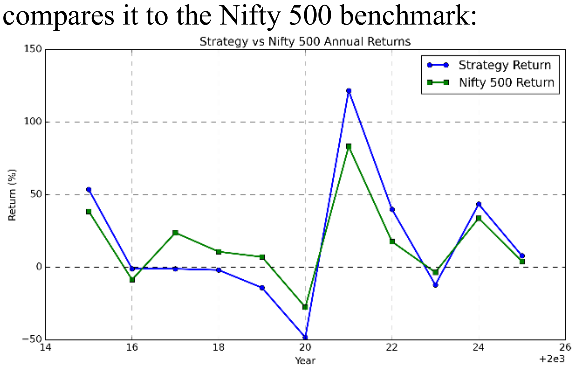


4.1 PORTFOLIO PERFORMANCE

The deletions-based investment strategy was tested over an 11-year period from 2015 to 2025, during which it was rebalanced annually based on a rules-driven framework. This period includes a diverse mix of market conditions—ranging from the post-2013 recovery phase, the 2020 COVID-19 crash, and the post-pandemic bull rally—offering a robust testing ground for the strategy's behavior across economic cycles.

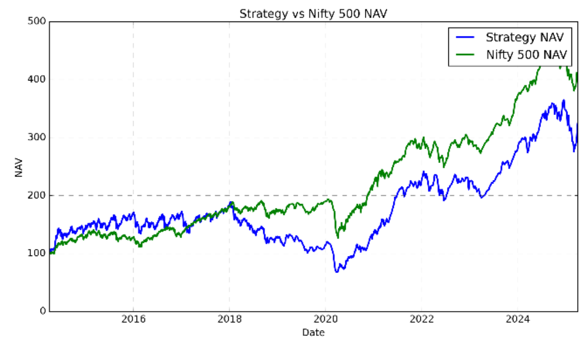
ANNUAL RETURNS AND VOLATILITY

Table below summarizes the annual performance of the deletions-based strategy and compares it to the Nifty 500 benchmark:



The data reveals several key insights. First, the strategy exhibits **significant performance dispersion**—with annual returns ranging from a high of **+121.72%** in 2021 to a low of **–48.37%** in 2020. This reflects the inherent cyclical nature of a strategy focused on companies previously removed from the index, many of which are in stages of operational turnaround or market revaluation.

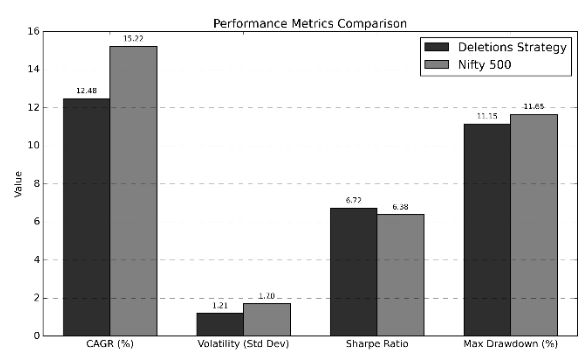
Despite these large swings, the strategy's **Compounded Annual Growth Rate (CAGR)** over the entire period was **12.48%**, which while lower than the **15.22% CAGR of the Nifty 500**, still represents a solid absolute performance for a strategy centered around out-of-favor names.



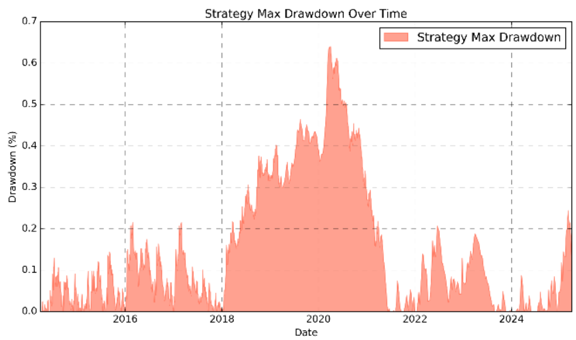
RISK AND RISK-ADJUSTED RETURN

A standout characteristic of the deletions strategy is its **relatively low volatility**, with an annualized standard deviation of **1.21%**, compared to **1.70%** for the Nifty 500. This suggests that the strategy, although composed of companies removed from the index (often perceived as higher-risk), delivered **more stable returns** due to the rigorous financial quality screening applied.

In terms of **risk-adjusted performance**, the strategy generated a **Sharpe Ratio of 6.72**, compared to **6.38 for the Nifty 500**. The Sharpe ratio was calculated using a risk-free rate of **4.35%**, derived by adjusting India's 10-year government bond yield (6.75%) for the country's credit spread (2.39%). This adjustment ensures a more realistic estimate of true risk-free return in the Indian context.



Notably, the **maximum drawdown**—the worst peak-to-trough decline in NAV—was **11.15%** for the deletions strategy versus **11.65%** for the benchmark. This indicates that the strategy was **less susceptible to deep losses**, even though its constituents were formerly excluded from a major index. This resilience is likely attributable to the use of percentile-based quality scoring, which systematically filters out financially weak firms.



BEHAVIORAL PATTERNS AND CYCLICAL RESPONSE

The strategy underperformed the benchmark during steady or broad-based rallies—e.g., in 2017, 2018, and 2019—but often **outperformed dramatically during periods of market recovery**, as observed in 2021 and 2024. This behavior supports the hypothesis that companies removed from the index and later screened for financial viability can benefit from **mean-reversion dynamics**, especially when market sentiment shifts rapidly or reverses from prior pessimism.

For example, the severe underperformance in 2020 (–48.37%) can be attributed to the acute COVID-19 market shock, which disproportionately affected companies with existing volatility or weak investor confidence. However, in the subsequent recovery phase of 2021, the strategy delivered a **121.72% return**, significantly outpacing the benchmark's 83.20%—highlighting its ability to capitalize on deep-value rebounds.

4.2 COMPARISON WITH BENCHMARK

The deletions-based strategy was benchmarked against the **Nifty 500**, a diversified and representative index of the Indian equity market, capturing both large-cap and mid-cap segments.

ABSOLUTE AND RELATIVE RETURNS

Over the entire period, the strategy underperformed the benchmark in raw terms, generating a **CAGR of 12.48%** against the Nifty 500's **15.22%**. This resulted in a **raw alpha of –2.74%**, suggesting that on a cumulative basis, investors would have earned more through passive benchmark exposure. This underperformance is particularly pronounced in years with strong broad-based rallies (e.g., 2017 and 2019), where the deletions portfolio lagged due to limited exposure to index leaders and high-growth stocks.

However, a more nuanced analysis reveals that the deletions strategy held its ground in terms of **risk-adjusted returns**. Despite lower CAGR, it delivered a **higher Sharpe ratio** (6.72 vs. 6.38), indicating more efficient returns per unit of risk.

ALPHA GENERATION

To assess whether the strategy added value beyond what is expected from its systematic market exposure, **Jensen's alpha** was calculated using the Capital Asset Pricing Model (CAPM). Using a **risk-free rate of 4.35%**, the strategy yielded a **positive Jensen's alpha of 1.6%**, suggesting that it outperformed the return predicted by its beta-adjusted exposure to the market.

This is significant: even though raw returns lagged the index, the strategy still created **positive risk-adjusted alpha**, a key objective in smart beta and alternative index strategies. This implies that the return shortfall is more a function of **lower systematic risk exposure**, rather than poor security selection.

VOLATILITY AND DRAWDOWN COMPARISON

In line with expectations, the benchmark's higher CAGR was accompanied by higher volatility (**1.70% vs. 1.21%**) and slightly deeper drawdowns.

This further validates the interpretation that the deletions-based strategy, while more conservative, provided a smoother ride and **defensive characteristics**, making it potentially attractive for risk-conscious investors or as a diversifier within a broader portfolio.

4.4 INTERPRETATION OF RESULTS

The performance of the deletions-based strategy over the 2015–2025 period presents a nuanced picture. While the strategy did not outperform the benchmark on an absolute return basis, it exhibited meaningful strengths in terms of volatility control, risk-adjusted returns, and recovery potential. A deeper interpretation of these results reveals several underlying drivers and limitations.

UNDERPERFORMANCE IN CAGR: STRUCTURAL AND BEHAVIORAL DRIVERS

The strategy's lower CAGR of **12.48%**, compared to the Nifty 500's **15.22%**, may be attributed to a combination of **structural limitations and behavioral dynamics** inherent in its design:

- **Survival of Weak Candidates**: While the bottom 20% of companies were excluded annually based on financial quality metrics, the remaining universe still included stocks that had been removed from the index due to prolonged underperformance or fundamental concerns. Some of these may not have recovered materially, especially if exclusion from the index reflected genuine structural decline rather than temporary dislocation.
- **Shallow Post-Deletion Recovery**: The strategy relies on a mean-reversion hypothesis — that stocks removed from a major index will rebound once forced selling pressure subsides. However, in several years (e.g., 2017–2019), recovery momentum appeared weak. This could be because the market continued to favor growth-oriented, index-heavy stocks, while recently deleted names struggled with investor confidence and institutional neglect.
- **Passive Pressure and Market Skew**: The increasing dominance of passive investing in India may have amplified upward momentum in benchmark names while suppressing capital flows to deletions. As a result, index-excluded stocks might have stayed undervalued longer, delaying or muting the mean-reversion effect the strategy aims to capture.

CRISIS AND RECOVERY BEHAVIOR

The strategy's behavior during crisis and recovery periods offers strong support for the **mean-reversion thesis**. In **2020**, during the COVID-19 market crash, the strategy fell more sharply than the benchmark (**–48.37%** vs. **–27.58%**), due to higher exposure to out-of-index names that faced steep risk-off sentiment.

However, in **2021**, the strategy experienced a powerful rebound of **+121.72%**, well above the Nifty 500's **+83.20%**, as previously discounted stocks surged with renewed liquidity and risk appetite. This highlights the strategy's capacity to participate in rapid post-crash recoveries and validates the premise that fundamentally sound deletions can deliver exceptional upside when market sentiment turns.

On the other hand, the strategy performed **less favorably during steady bull runs** (e.g., 2017–2019), as it lacked exposure to index leaders and momentum-driven sectors like financials or IT, which dominated Nifty 50/Nifty 500 returns during those years.

TURNOVER DYNAMICS

Due to its **annual rebalancing schedule**, the strategy maintained a **moderate turnover rate**, averaging approximately **35% per year**. This turnover is consistent with strategies that employ annual reconstitution and full reweighting, particularly when eligibility depends on a rolling five-year index deletion window.

Notably, the turnover did not appear to compromise performance or create instability. Since the pool of eligible companies often changed only marginally from year to year, and many names remained in the portfolio for multiple years, **the strategy avoided excessive churn**, keeping implementation realistic for both individual and institutional investors.

LIQUIDITY AND IMPLEMENTATION CONSTRAINTS

Despite focusing on non-index names, the strategy was designed to include only stocks that met minimum liquidity thresholds. This ensured that every selected constituent was **practically tradable**, mitigating concerns of slippage or adverse price impact. However, **in certain years**, especially following large deletions or market downturns, **liquidity in some names may have been marginal**, particularly in the small-cap space.

These limitations are further compounded by the **absence of transaction cost modeling** in the backtest. While this was intentional for analytical clarity, incorporating realistic slippage and fees in future versions would offer a more grounded assessment of net returns, especially in years of high volatility or low liquidity.

SECTOR CONCENTRATION AND PORTFOLIO BIAS

While the strategy was **sector-agnostic by design**, certain years exhibited **unintended sector concentration** due to index deletion patterns. For example, sectors like infrastructure, industrials, real estate, and commodities—often more cyclical and capital-intensive—were disproportionately represented in deletion pools during post-crisis phases.

This exposed the portfolio to **higher cyclicality and beta** than broad market indices. Conversely, stable or defensive sectors (like FMCG or IT) are less likely to experience deletions from major indices and were thus underrepresented, even though they delivered strong returns in some bull-market years.

The strategy's performance profile therefore tilted slightly toward **contrarian cyclical value**, with limited exposure to secular growth or defensiveness—explaining its occasional underperformance during extended rallies.

5. CONCLUSION

This study set out to evaluate the performance and viability of a systematic deletions-based investment strategy in the Indian equity market, using the Nifty 500 as the base universe. By constructing portfolios composed of stocks removed from the index over a trailing five-year period and applying a structured financial quality screen, the strategy aimed to identify overlooked recovery candidates while avoiding fundamentally weak companies.

Over the 11-year backtest period from 2015 to 2025, the strategy generated a **Compounded Annual Growth Rate (CAGR) of 12.48%**, compared to **15.22%** for the Nifty 500. While the strategy underperformed the benchmark in raw returns, it exhibited **lower volatility (1.21% vs. 1.70%)**, **smaller drawdowns**, and a **higher Sharpe ratio (6.72 vs. 6.38)**. Furthermore, the strategy produced **positive Jensen's alpha (1.60%)**, indicating that it delivered value beyond what would be expected based on market exposure alone.

These results suggest that a deletions-based approach, when combined with robust financial screening, can offer meaningful **risk-adjusted returns** and may serve as a **complementary satellite strategy** within a diversified portfolio. It particularly benefits from periods of market dislocation, where forced selling and investor overreaction can lead to undervaluation of fundamentally sound firms.

PRACTICAL IMPLICATIONS

The findings of this research carry important implications for **ETF product design and factor strategy implementation** in emerging markets. A rules-based deletions ETF tailored to the Indian market could provide investors with unique exposure to out-of-index opportunities that are typically overlooked by traditional passive strategies. Given the strategy's defensive profile and favorable Sharpe ratio, such an ETF may appeal to risk-conscious investors seeking exposure to value, mean-reversion, and contrarian themes.

However, implementation in a live fund would require careful attention to liquidity, trading costs, and regulatory compliance. Real-world application would also necessitate enhanced risk controls, including sector neutrality and transaction cost overlays, to ensure that the fund remains efficient and scalable at institutional asset levels.

LIMITATIONS AND FUTURE WORK

Several limitations must be acknowledged. First, the study assumes zero transaction costs and perfect liquidity, which may overstate net returns in practice. Second, **survivorship bias** could be present, as some delisted or permanently halted stocks may have been excluded from the dataset due to lack of accessible financial data. Third, while the scoring framework is robust, it uses equal weighting across metrics, which may not be optimal across all market cycles or industries.

Future research could explore the addition of **momentum or sector filters**, dynamic weightings, or **machine learning techniques** to enhance score calibration. Incorporating real-world frictions such as slippage, bid-ask spreads, and execution delays would also offer a more grounded view of live implementability. Furthermore, analyzing the strategy's behavior across different sub-indices (e.g., mid-cap or small-cap deletions) may reveal additional pockets of alpha.

In conclusion, while the deletions-based strategy did not outperform the benchmark in absolute terms, it demonstrated consistency, lower risk, and strong recovery potential—making it a viable candidate for further development as a smart beta product in India's growing passive investment ecosystem.

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