MUTUAL FUND

BUILT ON RULES

NJ's FACTOR BOOK

www.njfactorbook.com

2025

A BUSINESS BUILT ON TRUST

“To reach new heights, the foundation has to be strong.”

Over the last 30 years, NJ Group has been on a fulfilling path of discovery, growth, and evolution to emerge as one of the respected names in the financial services industry. The organisation stands today upon the foundations of upholding trust, passion for delivering, and the commitment to excellence. The interests of our investors and stakeholders continue to be the guiding light behind all our endeavours. With these virtues, we have created business opportunities for our partners, written success stories for investors, and thus transformed their lives.

The growth story of NJ Group progresses as we venture into newer horizons and businesses, driven by the same passion and commitment to serve and excel, doing what feels right for a larger cause. NJ Group feels privileged to give back to society through its social initiatives, especially by empowering the next generation with education. The journey continues, one step at a time, one path at a time, now by all of us together.

Started
1994

Employees
2200+

*As on 31st January 2025.

Mr. Neeraj Choksi (L) & Mr. Jignesh Desai (R)
(Co-Founders, NJ Group)

Chairman's Message

We have come a long way since the first edition of the NJ Factor Book was released in April 2022. As expected, Science has progressed across the globe with India's achievements outstripping the global pace.

At NJ Asset Management, we have moved towards establishing capacity that provides for the future. We now have a database that includes complete market and fundamental information of more than 1,200 companies spanning the last 20 years.

A mammoth effort has undergone to aggregate and define the data from various sources such that are stored in a uniform format to minimise errors, ensure completeness and get consistent results.

To facilitate the same we have created a state of the art data analytics platform, ***The NJ Smart Beta Platform,*** which not only allows our researchers to test the most complex factor based strategies using this database within minutes but also audit the output to gauge its accuracy.

The capabilities here also include portfolio attribution, and performance analytics to further dissect the attributes responsible for the result.

To ensure that the database and NJ Smart Beta platform are used to their potential, we have instituted best-in-class processes for the development and testing of parameters that form the foundation of our ability to derive and implement investment rules.

Using these capabilities, our researchers have tested thousands of portfolios from which we identified the best few for implementation. We have dedicated ourselves to continuous improvement of our data, platform, processes and of course, our portfolios.

The analytics we run corroborates our belief that investment portfolios must be built on a foundation of "Quality". The more we do, the clearer it becomes that owning quality stocks is the best and the most visible way to create long term wealth.

To reiterate our philosophy, we take "Quality" as our primary factor and within the universe of quality stocks we run other factors to improve the results.

As factor investing makes rapid strides globally, NJ Asset Management has participated in the evolution with the effective use of technology over more than a decade now. We continue to believe that a scientific approach to investing with a strong technology foundation has a high likelihood of success, aided by its inherent discipline and lack of emotional biases.

I am pleased to launch the fifth edition of NJ's Factor Book, a compilation of the insights and research conducted by NJ Asset Management's research team on various factors in India along with NJ AMC's proprietary Forensic and Governance Model. I hope you benefit from reading it and participating in the factor investing revolution.

Mr. Neeraj Choksi
Director & Chairman - NJ Asset Management Private Limited

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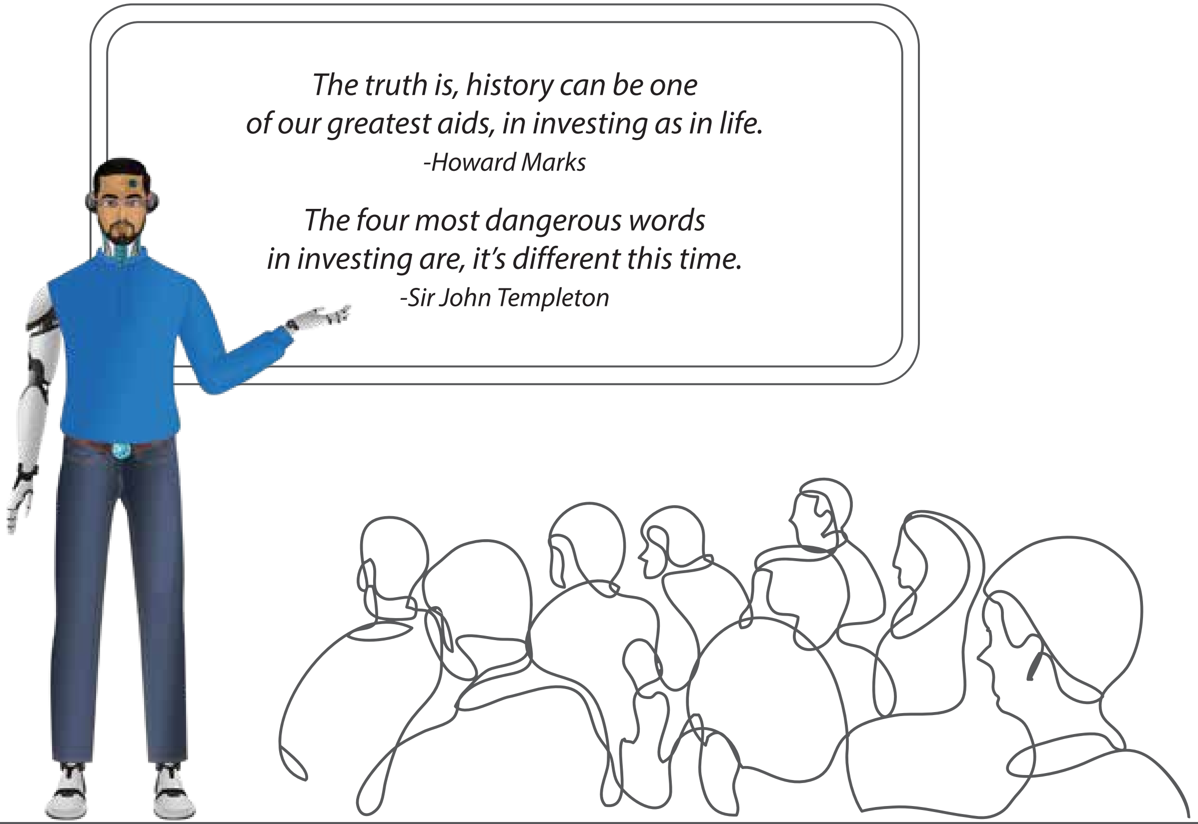
Preface

Most people accept that history is important and a knowledge of history is crucial to understanding the present and preparing for the future. In investing, a study of history provides crucial insights into market and investor behaviour. However, to a large extent, studying this history has only been of interest to market experts who have used it to guide their investment decisions.

With both quality and quantum of data increasing with time, it was inescapable that the role of data in investment decision making would only grow. However, the exponential growth of computing power over the last couple of decades super-powered this transformation.

Factor based investing, which relies on conducting increasingly complex analysis of ever growing amounts of data, is driven by this fortunate confluence of data and analytical capabilities.

This book tries to take you through the contours of how this came to be and where we see it headed.



1. What are **Factors?**

We don't have to be smarter than the rest.
We have to be more disciplined than the rest.
-Warren Buffett

You have to learn the rules of the game,
and then you have to play better than anyone else.
-Albert Einstein

For More Details

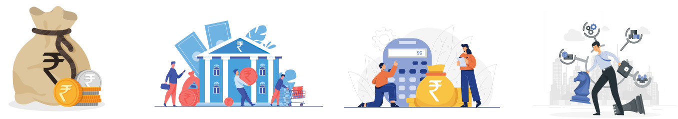
1. What are **Factors?**

1.1 Defining 'Factors' in an investment setting

We all praise Sachin's text-book style square cuts and master strokes, but is that enough to win matches for the Indian cricket team?

Apart from Sachin's quality batting, we also need Dhoni's low-volatility advice, Sehwag's strong scoring momentum, and Dravid's valuable "wall" for a victory.

When buying property as well, we generally do not make a decision solely based on the property's price, but also look at its location, safety and amenities among other aspects. Likewise, when making investment decisions, professionals tend to evaluate securities based on various parameters viz. price, volatility, relative value, earnings, growth, and liquidity among others. These different elements help explain the risks and returns of securities and are referred to as factors in the context of investing.



C	A	P	M
CAPITAL	**ASSET**	**PRICING**	**MODEL**

1.2 History and Evolution of Factor Investing: From Academia to Practice

Although buzzwords such as "investment factors," "factor funds," "smart/strategic beta" have recently gained popularity, factor investing was pioneered back in the 1960s. This era gave birth to many modern finance theories, including the seminal Capital Asset Pricing Model (CAPM). Factor investing, a methodical approach to choosing investments, has seen significant evolution since then.

CAPM and Future Advancements

Factor investing traces its origins to the 1960s, particularly the Capital Asset Pricing Model (CAPM). Developed by academics like Sharpe, Lintner, and Mossin, CAPM emphasised the role of market returns in explaining stock returns by claiming that a stock's expected return depends on its beta, a measure of its responsiveness to market movements.

Despite its contributions, CAPM faced challenges. CAPM explained a small portion of the returns, largely due to its many theoretical assumptions. CAPM's failure to explain various market phenomena, such as the Value Effect, Size Effect, and Momentum Effect, motivated academics to develop more sophisticated multi-factor models which explain risk and return based on factors other than beta.

Expanding the Paradigm with Fama and French

In response to CAPM's limitations, Fama and French introduced their seminal three-factor model in 1992. Going beyond market risk, it considered size and value factors as well. These developments can be considered as the official inception of multi-factor investing. Later, in 2015, they further refined the model with two additional factors: profitability and investment. This refinement allows for a broader understanding of expected asset returns, considering not just the stock’s systematic risk (beta) but also size, value, profitability, and investment characteristics.

Growing Factors and Competing Models

Factor investing continued to evolve with the addition of momentum in 1997 by Carhart and the introduction of alternative models like the Hou, Xue, and Zhang q-factor model.

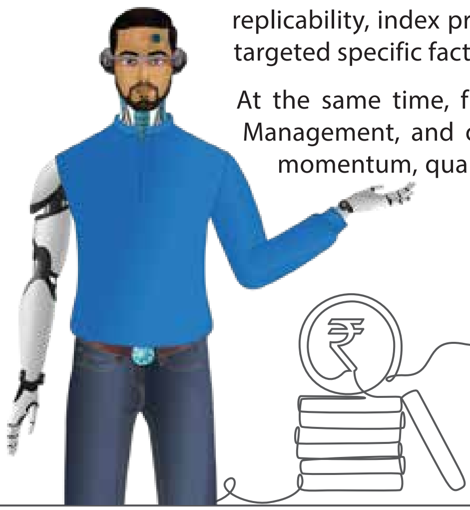
Factor investing is a rapidly evolving domain marked by the continuous introduction of new factor models and parameters. This expansion brings forth both opportunities and challenges.

Navigating the diverse array of factor parameters demands a discerning approach. The critical need is to distinguish genuine sources of excess returns from those potentially arising from data mining. This consideration holds utmost significance for researchers and practitioners, underscoring the need for rigorous methodologies and meticulous analysis.

Integration of Academic Research into Real-world Portfolio Management

Despite its academic success, factor investing remained largely theoretical throughout the 1980s and early 1990s. During this time asset managers were intrigued but hesitant in the face of implementation challenges. Data was scarce, and transaction costs for constructing portfolios based on these factors were considerably high.

By the mid-1990s, technology and data availability began to catch up. Asset managers like Dimensional Fund Advisors (DFA), led by David Booth and Rex Sinquefield, and influenced by Eugene Fama, were among the first to bring factor investing to life. DFA launched the US Small Cap Value Portfolio in 1993, one of the first funds to explicitly incorporate size and value factors. This successful incorporation of academic findings into action provided an early validation of factor-based investing.



The 2000s marked the creation of factor-specific indexes. Recognizing the need for transparency and replicability, index providers like MSCI, S&P Dow Jones, and FTSE Russell began designing indexes that targeted specific factors, such as value, momentum, and low volatility.

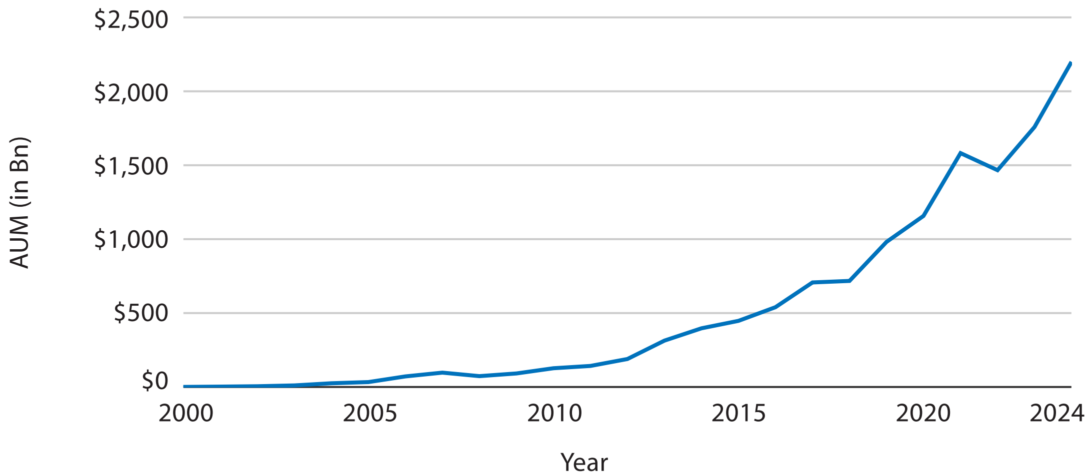
At the same time, financial institutions began to embrace factor investing. BlackRock, AQR Capital Management, and other industry giants launched multi-factor funds, combining factors like value, momentum, quality, and low volatility into a single strategy. The narrative shifted from "why factor investing?" to "how can we use it better?"

Later in 2014, Vanguard launched its Vanguard Value ETF (VTV) and Vanguard Small-Cap Value ETF (VBR), further democratizing factor-based investing by offering low-cost access to value and size factors.

The integration of academic research into real-world portfolio management has significantly influenced the growth of Smart Beta ETFs, as depicted in the chart and table. The chart illustrates the steady rise in the Assets Under Management (AUM) of equity Smart Beta ETFs in the U.S., with notable acceleration post-2010. This growth aligns with the broader acceptance of factor investing strategies by both institutional and retail investors.

The table further reinforces this growth trajectory. Over the last 15 years, Smart Beta ETFs have experienced a cumulative AUM increase of 23.54%, while since 2000, the growth stands at an impressive 36.97%. This trend signifies a maturing market where investors increasingly recognize the benefits of systematic, rules-based investing approaches.

Equity Smart Beta AUM Growth in the USA



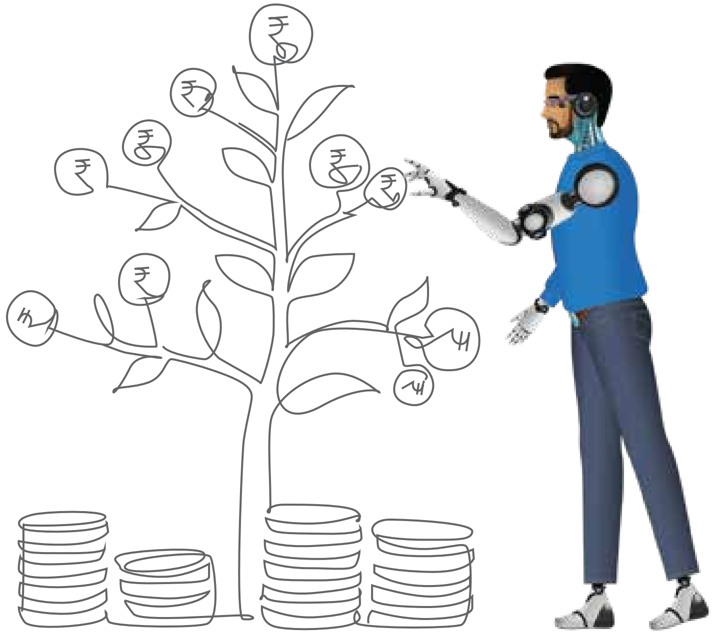
Source: Bloomberg Intelligence. Data as on 31st December 2024

Time Period	AUM Growth
Last 3 Years	11.60%
Last 5 Years	17.51%
Last 10 Years	18.66%
Last 15 Years	23.54%
Since 2000	36.97%

Source: Bloomberg Intelligence. Data as on 31st December 2024

Impact of Technology and Future Developments

Today, factor investing has become increasingly popular, with practitioners utilising and developing factor-based products due to their transparent and systematic rules and relatively low costs. The next few years will be interesting as we see how factor investing continues to evolve.



Technological and computational advancements have profoundly impacted factor investing, enhancing the capacity to process and analyse vast datasets, often referred to as big data, and identify complex patterns and relationships that drive asset returns. Machine learning and artificial intelligence (AI) have further revolutionised this field, allowing for the examination of non-linear relationships and the potential discovery of new, subtle factors. These technologies facilitate the development of sophisticated, data-driven investment strategies which also benefit risk management by improving the modelling of factor exposures and correlations. However, these technological advances also introduce new challenges, such as the risk of overfitting and the need for clear interpretability of complex models.

Factor investing has been pivotal in reshaping asset pricing and portfolio management. Originating from the market-centric view of CAPM, it has evolved into a multifactor perspective, notably influenced by Fama-French models. While successful in explaining market anomalies and aiding portfolio diversification, challenges persist—factor timing, market crowding, and the integration of non-financial data, such as ESG factors, pose complexities. The surge in factors and parameters raises concerns about data-snooping and the stability of factor premiums. Nevertheless, factor investing remains a vibrant area of research and practice, adapting to a changing financial landscape. The future will likely witness continued adaptation, leveraging technological advancements and data analysis to refine and potentially redefine critical factors for investment success. In this complex landscape, the connection between theoretical rigour and practical application remains crucial for investment success.

FACTORS USED IN VARIOUS FACTOR MODELS

	Market Beta	Value	Momentum	Size	Profitability/ Quality	Investment
Fama French 3 Factor (1993)	YES	YES	-	YES	-	-
Carhart Momentum (1997) Addition to 3 Factor Model	YES	YES	YES	YES	-	-
Fama French 5 Factor (2015) with Momentum	YES	YES	YES	YES	YES	YES
Hou et. al. Q-factor (2015)	YES	-	-	YES	YES	YES

1.3 Classifying a Parameter as an Investment Factor

Almost any parameter associated with the fundamental or market data of a company can be used as a factor. With potentially hundreds of factors available it is necessary to choose the most effective ones and avoid those that may be construed as random noises or one-time anomalies. Empirical developments in this space demonstrate that commonly accepted investment factors explain security returns cross-sectionally, over time, and across markets.

Common Attributes of Investment Factors

Any determinant of investment returns and/or risk must adhere to 5 unique attributes in order to be formally classified as an investment factor (Berkin & Swedroe, 2016). Investment factors must be,

PERSISTENT

The parameter must consistently explain returns over time i.e. its explanatory power must not fade away over time.

PERVASIVE

The parameter must explain returns across markets, economies, sectors, and geographies.

ROBUST

The parameter must not change its meaning or impact significantly with changes in the definition of its characteristics. For example, whether defined as the trailing price-to-earnings, price-to-book, or dividend yield, the meaning and economic significance of the Value factor must remain truly unambiguous.

INVESTABLE

Gaining exposure to the specific parameter must be easy and cost-efficient.

INTUITIVE

There must be an economic rationale/justification for getting exposure to that specific parameter.

1.4 Factor Categories: Macroeconomic Vs Style

Most investors classify investment factors into two broad categories, namely macroeconomic and style factors. As its name suggests, macroeconomic factors illustrate broad macroeconomic and financial elements of risk across several asset classes such as equities, fixed income, and gold. Common macroeconomic factors include interest rates, real GDP/economic growth, inflation, money supply and liquidity. Macroeconomic factors are typically used to determine asset allocation between different asset classes.

On the other hand, style factors are those specific to an asset class and used to select securities within the asset class. The most prevalent style factors for equities include:

- **Size** (small-cap, mid-cap, or large-cap companies)
- **Value** (undervalued stocks based on financial ratios)
- **Momentum** (stocks with strong recent performance trends)
- **Low Volatility** (low-risk stocks with stable returns)
- **Quality** (companies with strong financials like profitability, low debt, and high earnings stability).

We explore these in detail in the coming sections.

1.5 Understanding Rule-Based Investing, Active Investing, and Traditional Discretionary Investing in Mutual Funds

In the diverse world of mutual funds, investment strategies often fall into three broad categories: Rule-Based Investing, Active Investing and Traditional Discretionary Investing. While both aim to maximize risk-adjusted returns for investors, their approaches to achieving those returns differ significantly. Passive investing is yet another category of fund management, that aims to replicate a market index or benchmark viz. Nifty 50 or BSE Sensex, while minimizing costs and the tracking error for investors.

a. What is Active Investing

Active Investing relies on the expertise and judgement of fund managers. These managers perform qualitative and quantitative analyses, drawing on their experience, insights, and the broader economic context to make investment decisions. This could involve a detailed analysis of a company's management team, competitive advantages, market conditions, and growth potential. Active investing is characterized by its focus on outperforming a benchmark through active stock selection and market timing.

b. What is Rule-Based Investing

Rule-Based Investing, often associated with smart beta strategies, operates on predefined algorithms that systematically select stocks based on set factors and factor parameters. These factors include quantitative measures such as company size, value, momentum, volatility and quality. This approach is designed to take advantage of the consistent, repeatable opportunities that certain characteristics provide in the market. For instance, a rule-based fund might target high quality profitable companies that exhibit high price momentum and are relatively undervalued, investing in them until they no longer meet the criteria.

c. What is Passive Investing

Passive investing is a low-maintenance strategy focused on replicating the performance of a market index, such as the Nifty 50 or S&P 500. Instead of trying to beat the market, passive funds aim to match their returns by investing in the same set of securities as the index through different structures such as index funds and exchange-traded funds (ETFs). This strategy is characterized by its low cost, as minimal management fees are required due to the absence of active decision-making, and it also offers low tracking error, as it is specifically designed to closely replicate the performance of the chosen index.

Rule-Based Investing Vs. Traditional Discretionary Investing

Decision-Making Processes

The decision-making process in Rule-Based Investing is systematic and objective. It removes human bias from the equation, potentially providing more consistency and discipline. The rules are transparent, making it easier for investors to understand the strategy's decision-making process. Because the rules are set and do not change over time, it is possible to do backtesting over a long period of time which provides the ability to analyse the performance of the rules over a long historical period.

Traditional discretionary investing, however, is subjective and can be heavily influenced by the fund manager's convictions. This could potentially lead to biases or emotional decisions that may not always align with market performance. Nonetheless, the human element allows for nuanced understanding and the ability to pivot strategy based on real-time market insights. Here investors often look at the performance of the fund or the fund manager over the past long period to analyse a manager’s decisions and its impact.

Roles and Expertise

Rule-based investing relies heavily on quantitative models developed by data scientists and financial analysts. These professionals backtest algorithms against historical data to ensure they can generate high risk adjusted returns across various market conditions.

Traditional discretionary funds, conversely, rely on the acumen of seasoned fund managers who can interpret complex market data and news to identify investment opportunities. Fund managers are often supported by research analysts who provide information to enable the manager in portfolio decision making.

Performance and Risk

Performance between the two can vary significantly under different market conditions. More often than not, the two styles offer a diversification opportunity that can ease the impact of volatility over the short term while participating in equity growth over the long term. Risk management is another differentiator.

Rule-based strategies with their innate discipline and lack of human intervention can ensure that risks are limited to acceptable levels. Discretionary managers, meanwhile, may adjust their strategies based on their perception of risk, potentially allowing for more diverse risk outcomes.

Transparency

Rule-based strategies typically afford investors a clear view of the investment process and criteria used in selecting the portfolio.

Traditional discretionary investing is less predictable, as it may not always be clear why a fund manager chose a particular investment over another.

Historical Context and Evolution

Both investment styles have a rich history and have evolved over time. Rule-based strategies have become more sophisticated with the advent of big data, faster computing power and advanced analytics, while discretionary investing has benefited from increased global connectivity and real-time information flow. However, with markets becoming more efficient, the advantage that discretionary managers enjoyed earlier has been steadily shrinking.

In conclusion, rule-based factor investing and traditional discretionary investing in mutual funds each have their merits and drawbacks. Investors should carefully consider their unique attributes, including the decision-making processes, costs, and potential for risk and return, before deciding which investment style best suits their portfolio.

Key Differences among Investment Strategies

	Active Investing	Rule-Based Investing	Passive Investing
Investment Decision-Making	Relies on human judgment, research, and discretionary decisions by portfolio managers.	Based on pre-defined, systematic rules or models, often derived from factors.	Follows a benchmark index with minimal decision-making, replicating its performance.
Objective	To outperform the market (generate alpha) through stock-picking and market timing.	To outperform traditional market-cap-weighted indices by capturing specific factor premiums (smart beta).	To match the performance of a benchmark index (beta replication).
Use of Factors	Not very predominant	Predominant	Depends on the Benchmark Index
Portfolio Characteristics	Different from Benchmark	Different from Benchmark	Same as Benchmark

Implementation of Rule-based Investing

Rule-based investing can be executed in two ways: active rule-based investing and passive rule-based investing. While both passive and active rule-based investing are rooted in systematic, factor-based approaches, they differ significantly in their execution and adaptability.

a. Active Rule-based Investing:

Active Rule-based Investing combines the structured discipline of rule-based strategies with the adaptability of active management. While the portfolio starts with predefined factors, fund managers actively manage and adjust these rules in response to changing market conditions. This dynamic approach allows for seizing new opportunities or mitigating emerging risks.

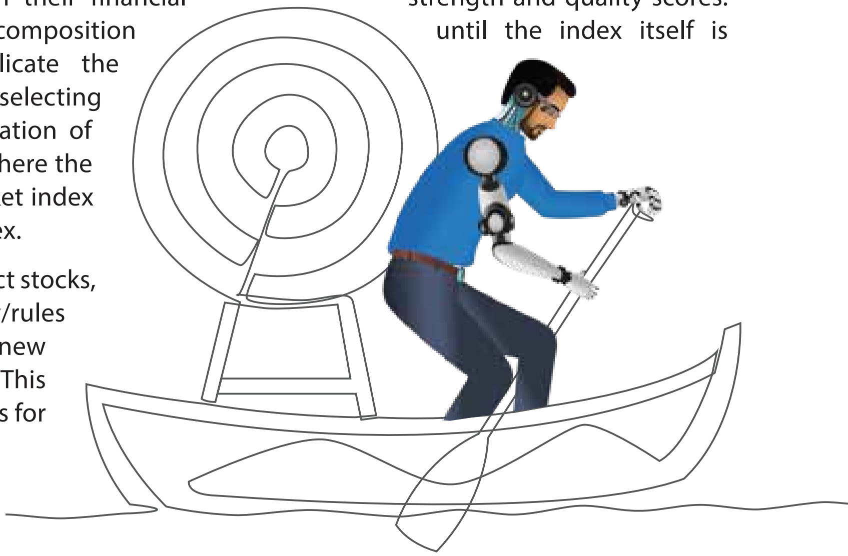
At NJ AMC, our schemes and investment approaches employ a robust, proprietary algorithm to identify stocks based on predefined factors like quality, value, momentum, and low volatility. These algorithms are the "rules"—a systematic, data-driven map to guide the fund's investment decisions. However, what sets this approach apart is its flexibility. The fund's managers don't just follow the rules rigidly; they actively adapt them as the market environment evolves. If new economic trends emerge or certain factors lose their relevance, the methodology is fine-tuned to seize fresh opportunities or mitigate risks.

b. Passive Rule-based Investing:

Passive Smart Beta Investing, on the other hand, involves replicating an index or a fund following a rule-based approach, predefining factor methodology used to construct its portfolio. The rules for passively replicating an index are typically fixed, proportionately replicating the index constituents, offering minimal flexibility.

For example, an Index Fund or an ETF tracking the Nifty 200 Quality 30 doesn't try to outsmart the rule-based index, instead, it seeks to mirror the performance of the Nifty 200 Quality 30 Index, which itself is designed to select 30 high-quality companies from the Nifty 200 based on their financial strength and quality scores. Once the portfolio is constructed, the fund maintains its composition until the index itself is rebalanced. The fund applies static rules to replicate the high-quality companies of the Index, without actively selecting the companies and the rules. This passive implementation of Rule-based investing is akin to pure passive investing where the fund manager mirrors the performance of a broad market index such as Nifty 500 instead of a rule-based smart beta index.

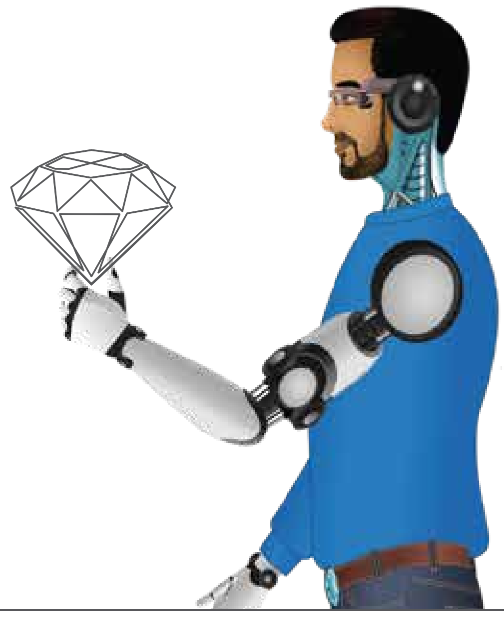
Active Rule-based Investing uses predefined factors to select stocks, but unlike Passive Rule-based Investing, the methodology/rules can be adjusted as and when needed to reflect new opportunities or changes in the market environment. This flexibility inherent in the Active Rule-based Investing allows for a more tailored application of rule-based investing principles for better adaptation to evolving trends while still maintaining systematic discipline.



2. Quality **Factor**

Quality is never an accident.
It is always the result of intelligent effort.
-John Ruskin

It is hard to make a good return over the long term by investing in poor-quality or even average businesses.
-Terry Smith



For More Details

2. Quality **Factor**

2.1 What is 'Quality' Investing?

Quality investing is a strategy where investors look for companies that have strong and enduring characteristics. These characteristics often include robust financial health, strong management, a competitive advantage, and the potential for growth and profitability over the long term. The main idea is to invest in companies of "high quality" rather than just looking for stocks that are cheap or undervalued. This strategy often involves a longer-term perspective, as quality companies are expected to provide stable and consistent returns over time.

In simpler terms, imagine you're shopping for a car. Quality investing would be akin to choosing a vehicle known for its reliability, fuel efficiency, and excellent safety ratings, rather than going for the cheapest car you can find.

Research in the realm of quality investing has grown over the years. Scholars and financial analysts have sought to define and measure 'quality' in a more systematic and rigorous manner. Various metrics and frameworks have been developed to evaluate the quality of companies from an investment perspective.

The first challenge is of course, defining 'Quality'. Researchers have collaborated with practitioners to define what constitutes quality in a company. Common attributes include strong and consistent profitability, low debt levels, efficient use of capital and stable earnings.

The next step, equally challenging, is to measure quality. Quality can tend to mean different things to different people. However, various frameworks and parameters have been accepted as universally acceptable over time. Common parameters include return on equity (ROE), consistency of profits and dividends, measures of cash flow and debt to equity ratios, among others.

These definitions and the parameters together constitute the 'Quality Factor", which focuses on quality as a distinct factor that can drive stock returns. The quality factor isolates the returns attributable to investing in high-quality stocks. There's substantial research analysing the performance of quality investing strategies over time, across different market conditions, and in comparison to other investing strategies like value or momentum investing.

Quality investing is also associated with lower risk compared to other strategies, and research has explored the risk-return profile of quality investing, often finding a favourable trade-off. Research has also explored how quality investing can be integrated with other investment strategies, such as value or momentum investing, to potentially enhance returns or reduce risk. In addition, the behavioural aspects of quality investing have also been explored, investigating how investor perceptions and biases can impact the assessment of quality and subsequent investment decisions.

The field is continually evolving with ongoing research aiming to refine the understanding and application of quality investing, exploring its implications across different market segments and geographic regions, and integrating newer data and analytical techniques like machine learning to enhance quality assessment and investment decision-making.

2.2 International experience with Quality Investing

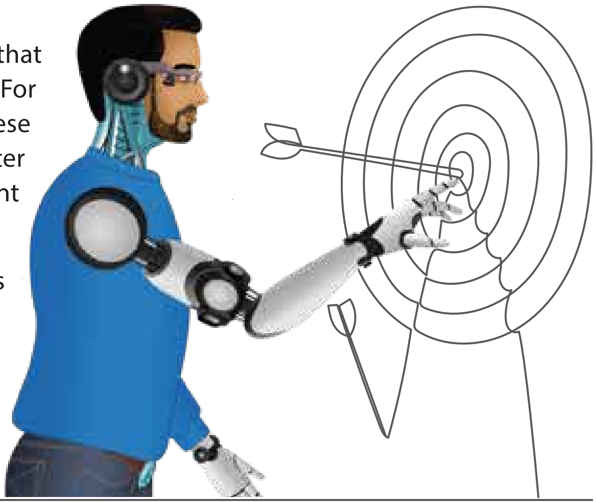
Quality investing, as a strategy, focuses on selecting companies that exhibit robust and enduring characteristics, with an aim to achieve stable and consistent returns over the long term. Various data points and analyses have shed light on the performance of quality investing across different time frames and market conditions:

1. Recent Performance: On August 31, 2022 and January 31, 2023, companies categorised as high-quality outperformed the S&P 500 by 3.7 percentage points, hinting at the possibility of quality stocks entering a new cycle of outperformance. (Nelson, J. (2023)).

2. Long-term Outperformance: A study spanning 18 years from 2002 to 2020 and regions including North America, Europe and the pacific region including Japan, found that quality factor outperformed its benchmark by 2.8% per annum, with an information ratio of 0.81, showcasing a consistent long-term outperformance of quality investing (Lepetit, F., Cherief, A. & Ly, Y. and Sekine, T. (2021)).

3. Performance in times of stress: Data from 2001 to 2020 indicated that quality and growth stocks tend to fare better following a recession. For instance, during the Global Financial Crisis (2007-2009), investors in these stocks, on average, were more likely to recoup their losses faster compared to the broader market. (Motley Fool Wealth Management (2023)).

4. Performance during Market Turbulence: A recent analysis indicated that quality investing demonstrated resilience amidst market turbulence over the past decade, which included a bear-market episode, rising inflation, and fluctuating rates. (Conway, C (2023)).



5. Unusual Performance in 2022: The first half of 2022 witnessed an unusual performance of quality investing. Typically, during market sell-offs driven by geopolitical issues or inflation concerns, investors find refuge in high-quality companies. However, in 2022, high-quality companies didn't provide the expected cover. This underperformance was especially noticeable during April and May 2022, where global markets saw negative sector-relative performance in the highest quintile of quality, compared to the universe average.

The underperformance of quality in 2022 was less about high-quality being out of favor but more about the strong performance of value stocks, as value and quality tend to be negatively correlated. (Zani, C (2022)).

These data points and analyses showcase the enduring performance of the quality factor across different market scenarios and time frames.

2.3 Indian Experience with Quality Investing

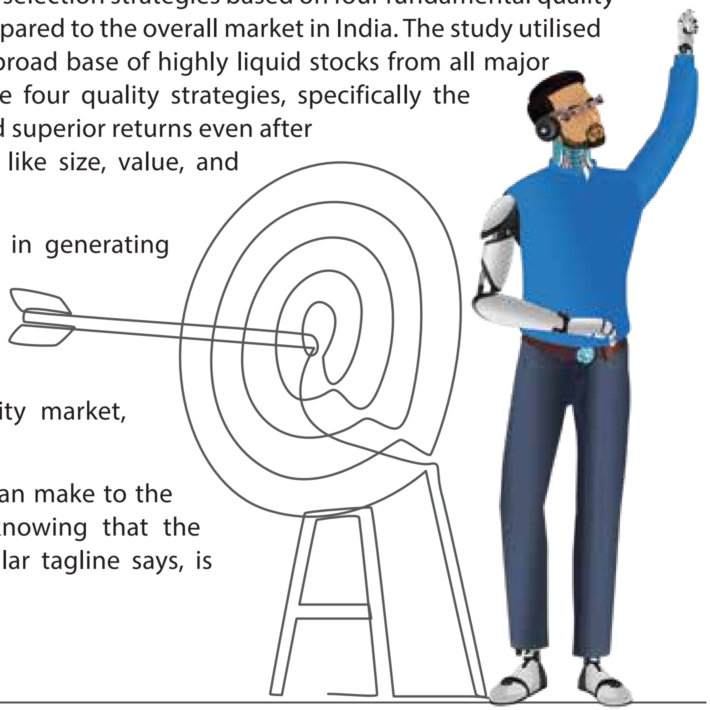
The performance of quality investing in the Indian market has been explored through various studies, providing insights into its effectiveness and comparison with other investment factors:

1. Quality Factor Performance: A study from the Indian Institute of Management Ahmedabad (IIMA) reported that the Quality Minus Junk (QMJ) factor yielded a four-factor alpha of 0.92% per month, significantly outperforming other widely recognized factors like size, value, and momentum. In a long-only framework, the Quality factor earned an alpha of 0.69% per month, indicating a significant level of outperformance as judged by established thresholds. (Jacob, J., Pradeep K.P., & Varma, J. (2022)).

2. Stock Selection Strategies: Another study explored stock selection strategies based on four fundamental quality indicators to assess if they can generate superior returns compared to the overall market in India. The study utilised a sample of stocks from the BSE 500 index, representing a broad base of highly liquid stocks from all major industries in the Indian economy. It found that two of the four quality strategies, specifically the Grantham Quality indicator and Gross Profitability, generated superior returns even after controlling for market returns and other common factors like size, value, and momentum. (Lalwani, V., & Chakraborty, M. (2018)).

These studies highlight the potential of quality investing in generating superior returns in the Indian market, showcasing the effectiveness of certain quality indicators and the significant outperformance of the quality factor over other market factors. The data underscores the relevance of quality investing as a viable strategy in the Indian equity market, aligning with global trends in quality investing performance.

However, the greatest contribution that the quality factor can make to the portfolio is the peace of mind that an investor gains knowing that the possibility of rude surprises is minimised. That, as a popular tagline says, is "priceless".

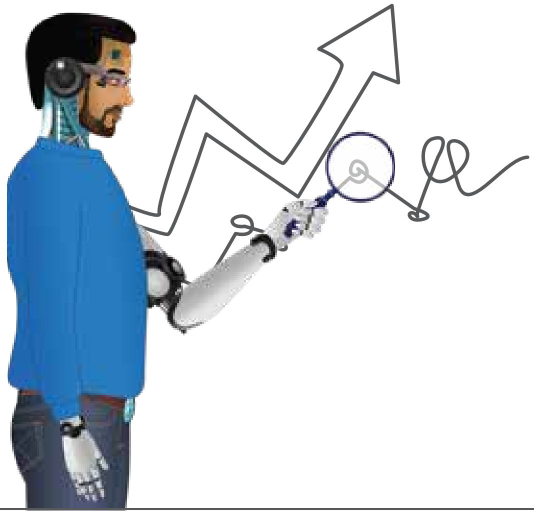


2.4 How is 'Quality' measured?

The below table shows that quality factor commercial indices are not all the same. They have different inputs and methodologies, which often lead to different outcomes.

Index Details	Factor Characteristics	Methodology
Index Name: S&P 500 Quality Index Index Provider: S&P Dow Jones Indices LLC	ROE (TTM), Balance Sheet Accruals Ratio (Change in NOA/Avg NOA), Leverage (Total Debt/BVE)	Tilt S&P 500 Index (capitalisation-weighted) towards 100 constituents with their weights based on the product of their market cap in the Parent Index and Overall Quality (based on the 3 Quality metrics)
Index Name: Russell 2000 0.4 Target Exposure Quality Factor Index Index Provider: FTSE Russell	Profitability (Only ROA for profitability in case of Financial and RE companies): ROA, Accruals Ratio, Change in ATO; Leverage: Leverage Ratio (OCF/Total Debt)	Tilt Russell 2000 Index (capitalisation-weighted) based on a combined Quality Z-score
Index Name: NIFTY100 Quality 30 Index Index Provider: NSE Indices Ltd	ROE, Financial Leverage (D/E), and last 5-Yr EPS growth variability	Choose 30 stocks from Nifty 100 Index (capitalisation-weighted) based on their quality scores and weight them according to the product of their free-float market cap and Quality Z-Score
Index Name: Fidelity U.S. Quality Factor Index Index Provider: Fidelity Investments Inc.	For Non-Banks: FCF Margin, ROIC, FCF Stability; For Banks: ROE, Debt to Assets	Select high quality stocks, from top 1,000 stocks in the U.S., based on a composite score. Security weights determined on the basis of an overweight adjustment (identical for all stocks within a sector) and their market capitalisations
Index Name: MSCI India Quality Index Index Provider: MSCI Inc.	ROE, Debt-to-Equity, Earnings Variability	Tilt MSCI India Index (capitalisation-weighted) towards high Quality constituents with weights equal to their product of market capitalisations weight in MSCI India Index and Composite Quality Score

Source: FTSE Russell, MSCI Inc, S&P Dow Jones Indices LLC, NSE Indices Ltd. & Fidelity Investments Inc.



2.5 Does the Quality Factor work?

The inherent inconsistency in the definition of 'quality', make it difficult to gauge the true determinants of the quality premium i.e. the higher excess returns by high quality companies vis-a-vis companies of low quality. Academics and practitioners, including index providers, generally evaluate a stock's quality based on its financial and accounting/reporting quality.

Hsu, Kalesnik, and Kose (Hsu et al., 2019) examined the quality premium by comparing seven different traits, namely profitability, earnings stability, capital structure, growth, accounting quality, payout/dilution, and investment.

Based on their study, covering the US, Global Developed, Japan, Europe, and Asia Pacific ex-Japan over the period 1990-2016 (1963-2016 for the US), they concluded that quality metrics focusing on capital structure, earnings stability and growth had little impact on the quality premia. On the contrary, profitability, accounting quality, payout/dilution, and investments (capital expenditures) tend to drive the quality premium.

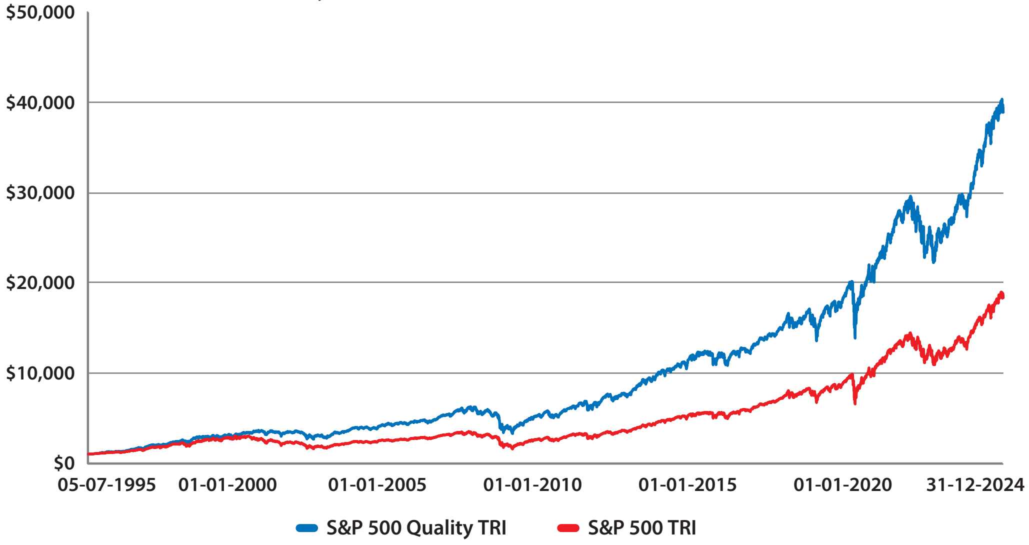
In India, quality as a factor has worked well especially since the Great Financial Crisis of 2008. During the tumultuous market conditions of that period, some stocks outperformed others by a wide margin and a common thread that connected these were their superior profitability, margin and debt indicators. This has also drawn attention to the factor leading to its incorporation into most investment processes.

2.6 Performance of Quality Factor Across Markets: USA, Europe, and India

The performance of the Quality factor across the USA, Europe, and India has demonstrated consistent outperformance against their respective benchmarks, highlighting its effectiveness as a long-term investment strategy.

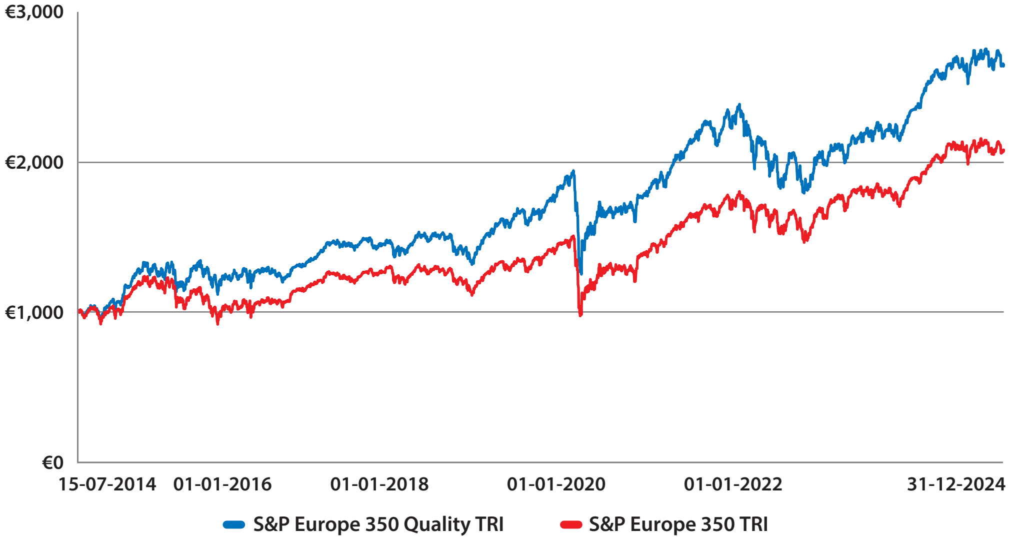
Across all the markets the quality factor index has historically outpaced their respective benchmark, particularly during periods of economic uncertainty, showcasing the resilience of high-quality companies with strong financials. The strong performance of the Quality index in comparison to respective benchmarks in downturns, reinforces the defensive nature of Quality stocks.

Quality Vs Market: Value of $1000 Invested



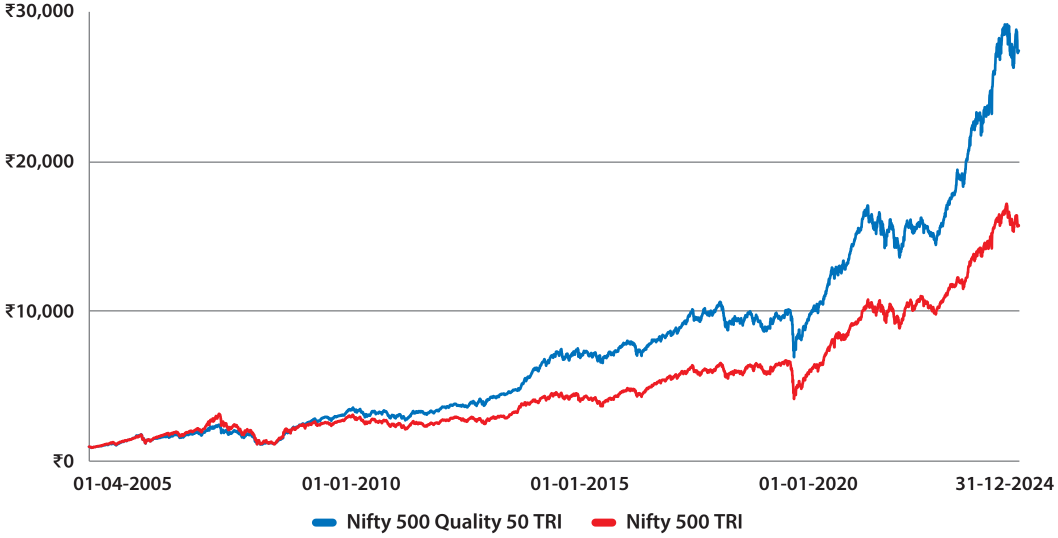
Source : Bloomberg. This chart depicts the growth in the NAV of S&P 500 Quality TRI vis-a-vis that of the S&P 500 TRI over the period 5th July 1995 to 31st December 2024. All the NAVs are in USD and have not been converted to INR. All the indices have been scaled to $1,000 as of 5th July 1995. Past performance may or may not be sustained in future and is not an indication of future return.

Quality Vs Market: Value of €1000 Invested



Source : Bloomberg. This chart depicts the growth in the NAV of S&P Europe 350 Quality TRI vis-a-vis that of the S&P Europe 350 TRI over the period 15th July 2014 to 31st December 2024. All the NAVs are in EUR and have not been converted to INR. All the indices have been scaled to €1,000 as of 15th July 2014. Past performance may or may not be sustained in future and is not an indication of future return.

Quality Vs Market: Value of ₹1000 Invested



Source : NSE. This chart depicts the growth in the NAVs of Nifty 500 Quality 50 TRI vis-a-vis that of the Nifty 500 TRI over the period 1st April 2005 to 31st December 2024. All the indices have been scaled to ₹1,000 as of 1st April 2005. Past performance may or may not be sustained in future and is not an indication of future return.

Period-wise Summary of Factor Performance: Quality Vs Market

Region	Period	Annualised Return (%)		3-Year Median Rolling Return (%)		10-Year Median Rolling Return (%)	
		Quality	Market	Quality	Market	Quality	Market
USA	Jul 5, 1995 - Dec 31, 2000	26.42	19.32	27.24	25.80	-	-
	Jan 1, 2001 - Dec 31, 2006	6.49	2.94	10.40	8.98	-	-
	Jan 1, 2007 - Dec 31, 2012	6.42	2.29	4.56	1.58	-	-
	Jan 1, 2013 - Dec 31, 2018	11.20	12.15	9.86	10.90	-	-
	Jan 1, 2019 - Dec 31, 2024	17.81	16.95	11.64	10.35	-	-
	Entire Period	13.21	10.36	11.81	11.20	11.00	7.98
Europe	Jul 15, 2014 - Dec 31, 2018	6.92	2.97	6.39	3.61	-	-
	Jan 1, 2019 - Dec 31, 2024	11.90	10.55	8.34	8.99	-	-
	Entire Period	9.75	7.25	8.44	7.60	10.09	7.60
India	Apr 1, 2005 - Dec 31, 2012	18.83	14.79	16.46	8.58	-	-
	Jan 1, 2013 - Dec 31, 2018	16.45	12.75	16.29	13.11	-	-
	Jan 1, 2019 - Dec 31, 2024	19.21	17.20	20.74	19.28	-	-
	Entire Period	18.23	14.96	16.37	13.11	16.49	12.75

Source : Bloomberg, NSE. Past performance may or may not be sustained in future and is not an indication of future return. The S&P 500 Quality TRI, S&P Europe 350 Quality TRI, & Nifty 500 Quality 50 TRI are used to represent the Quality index for the USA, Europe and India regions respectively. The S&P 500 TRI, S&P Europe 350 TRI, & Nifty 500 TRI are used to represent the market index for the USA, Europe and India regions respectively.

2.7 NJ's Quality Factor - NJ Quality+ Model

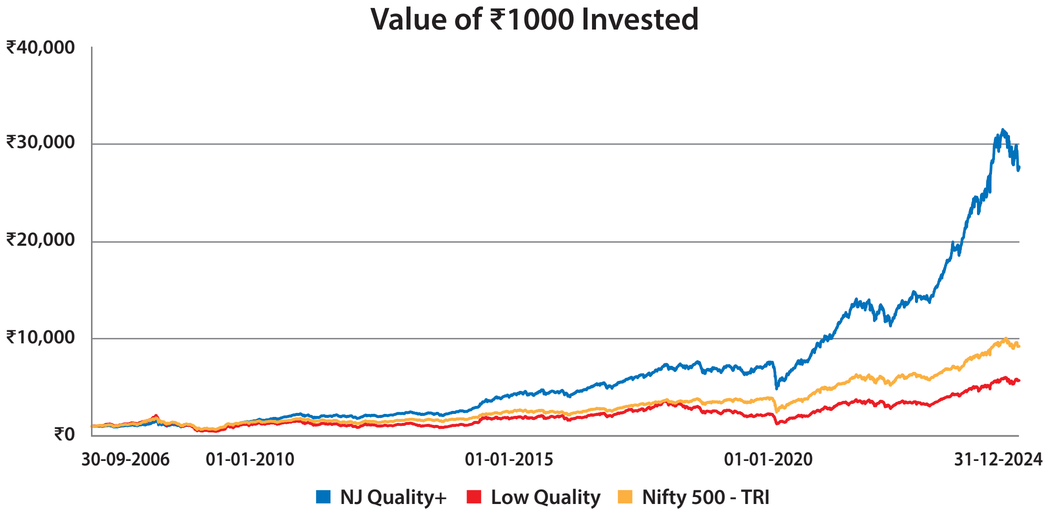
Both intuition and experience with the Quality factor are extremely strong. At the same time, one needs to choose the best parameters to ascertain the presence of quality carefully. The goal is clearly to target stocks that exhibit superior profitability parameters and generate value for the shareholders through various markets and business cycles. These include profitability, cash flow, and related attributes like Return on Investment, Return on Capital Employed, Dividend Payout, Interest Coverage among others that are derived from a company's financial statements.

With these parameters, there is often a need to measure the performance of financials and non-financials differently and look at sector-specific ratios for them.

The NJ Quality+ model uses a combination of quality metrics to categorise and rank stocks. The quality parameters used are Leverage, Return On Equity (ROE) And Dividend Payout Ratio. The NJ Quality+ model chooses the Top 100 stocks with the highest quality characteristics from the Top 500 stocks by free-float market cap universe and constructs an equal weighting model.

We have also created a Low Quality Model Portfolio which is similar in construction to the NJ Quality+ model but chooses the Bottom 100 lowest quality stocks. This would help us in comparing the risk and return of high-quality vs low-quality stocks.

The models display the following characteristics vis-a-vis the benchmark Nifty 500 TRI.

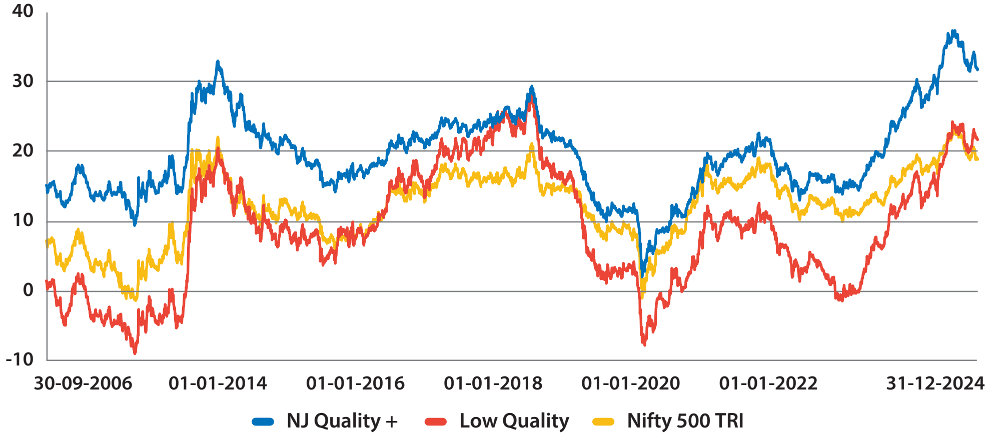


Source: Internal research, Bloomberg, CMIE, National Stock Exchange, NJ's Smart Beta Platform (in-house proprietary model of NJAMC). Calculations are for the period 30th September 2006 to 31st December 2024. NJ Quality+ Model and Low Quality Model are proprietary methodologies developed by NJ Asset Management Private Limited. The methodologies will keep evolving with new insight based on the ongoing research and will be updated accordingly from time to time. Past performance may or may not be sustained in future and is not an indication of future return. The above is only for illustration purposes and should not be construed as indicative return of offering of NJ Asset Management Private Limited.

	ROE (%)	ROCE (%)	Dividend Payout(%)	Current Ratio	Debt/Equity (%)
NJ Quality+	25.11	27.24	45.54	2.05	25.02
Low Quality Model	11.35	9.62	9.20	1.58	108.81
Nifty 500 TRI	16.58	18.37	23.67	2.05	124.24

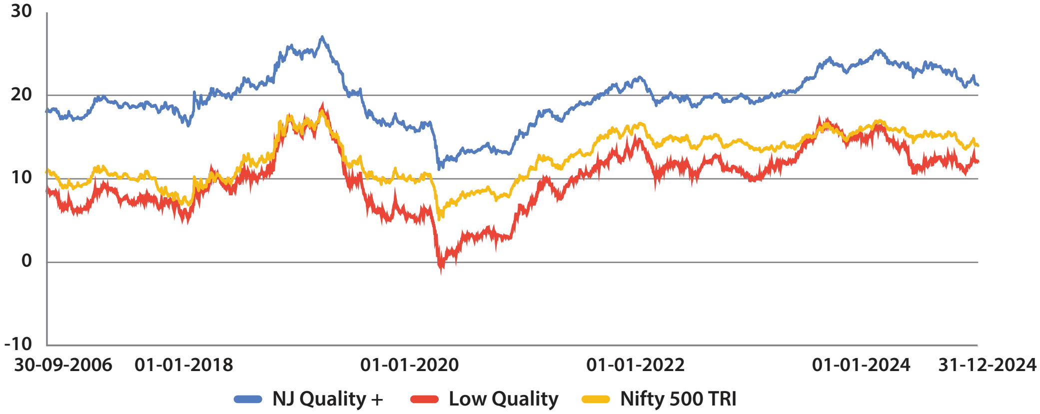
Source: Internal research, Bloomberg, CMIE, National Stock Exchange. Factor parameters calculated as on 31st December 2024. For Nifty 500 TRI, NJ Quality+ Model and Low Quality Model factor definitions are the average of its constituents. ROE is calculated by dividing the net income with the shareholders equity. ROCE is calculated by dividing the profit before interest & taxes by capital employed. Lending companies are not considered in calculation of ROCE. Dividend Payout is calculated by dividing the dividend paid by profit after tax. Current Ratio is calculated by dividing the current asset by current liabilities. Financial companies are not considered in calculation of current ratio. Debt to Equity is calculated by dividing the total liabilities by total shareholders equity, excluding Lending Companies. Outliers are not considered while calculating the numbers. Past performance may or may not be sustained in future and is not an indication of future return. NJ Quality+ Model and NJ Low Quality Model are proprietary methodologies developed by NJ Asset Management Private Limited. The methodologies will keep evolving with new insight based on the ongoing research and will be updated accordingly from time to time.

NJ Quality+, Low Quality vs Nifty 500 TRI : 5-Yr Rolling Returns



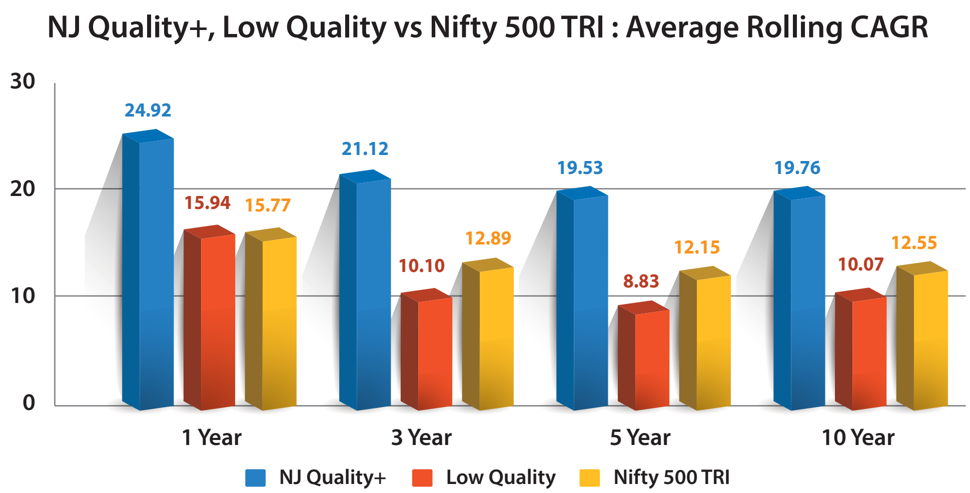
Source : Internal research, Bloomberg, CMIE, National Stock Exchange of India, NJ's Smart Beta Platform (in-house proprietary model of NJAMC). 5-Yr CAGRs are calculated for the period 30th September 2006 to 31st December 2024 and have been rolled on a daily basis. Past performance may or may not be sustained in future and is not indication of future return. NJ Quality+ Model and Low Quality Model are proprietary methodologies developed by NJ Asset Management Private Limited. The methodologies will keep evolving with new insight based on the ongoing research and will be updated accordingly from time to time.

NJ Quality+, Low Quality vs Nifty 500 TRI : 10-Yr Rolling Returns

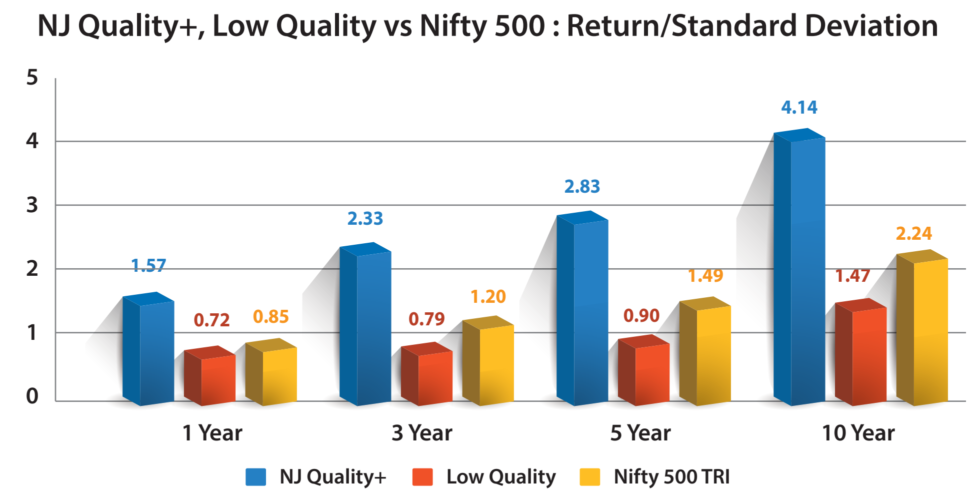


Source : Internal research, Bloomberg, CMIE, National Stock Exchange of India, NJ's Smart Beta Platform (in-house proprietary model of NJAMC). 10-Yr CAGRs are calculated for the period 30th September 2006 to 31st December 2024 and have been rolled on a daily basis. Past performance may or may not be sustained in future and is not indication of future return. NJ Quality+ Model and Low Quality Model are proprietary methodologies developed by NJ Asset Management Private Limited. The methodologies will keep evolving with new insight based on the ongoing research and will be updated accordingly from time to time.

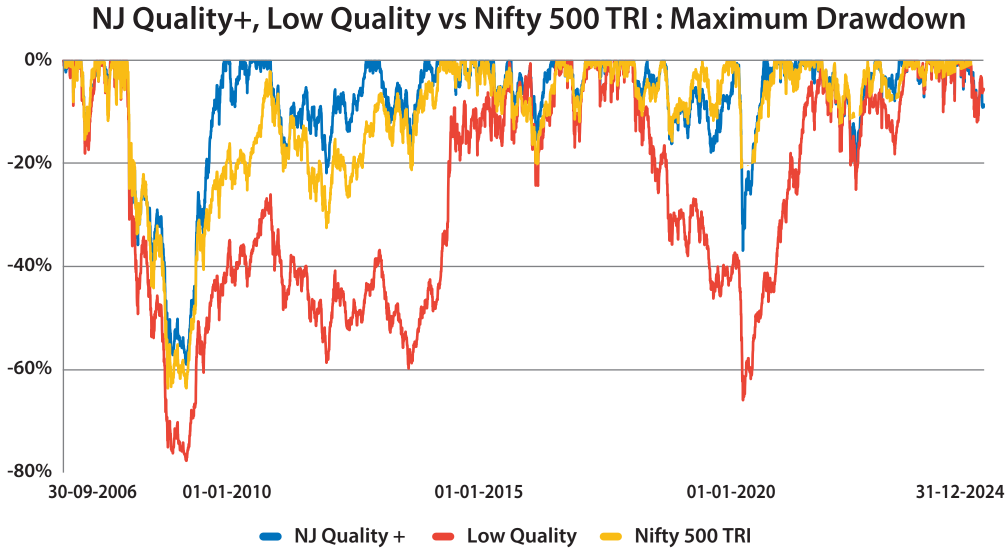
One can see from the charts above that while there is some cyclicality in the performance of the quality factor, it appears to sustain a more stable relationship with the index. As with all other factors, efforts to improve the way quality is measured are continuously underway among academics as well as practitioners.



Source : Internal research, Bloomberg, CMIE, National Stock Exchange of India, NJ's Smart Beta Platform (in-house proprietary model of NJAMC). CAGRs are calculated as the average CAGR based on the rolling CAGRs (rolled daily) calculated for the respective holding periods i.e. 1, 3, 5, and 10-Yr rolling CAGRs. The period for calculation is 30th September 2006 to 31st December 2024. Past performance may or may not be sustained in future and is not an indication of future return. NJ Quality+ Model and Low Quality Model are proprietary methodologies developed by NJ Asset Management Private Limited. The methodologies will keep evolving with new insight based on the ongoing research and will be updated accordingly from time to time.



Source : Internal research, Bloomberg, CMIE, National Stock Exchange of India, NJ's Smart Beta Platform (in-house proprietary model of NJAMC). The Return/-Standard Deviation ratios have been calculated by dividing the respective rolling returns (rolled daily) by the standard deviation of the corresponding rolling returns, calculated over the period 30th September 2006 to 31st December 2024. Past performance may or may not be sustained in future and is not an indication of future return. NJ Quality+ Model and Low Quality Model are proprietary methodologies developed by NJ Asset Management Private Limited. The methodologies will keep evolving with new insight based on the ongoing research and will be updated accordingly from time to time.



	NJ Quality+	Low Quality	Nifty 500 TRI
Maximum Drawdown	-59.05%	-77.79%	-63.71%

Source: Internal research, Bloomberg, CMIE, National Stock Exchange of India, NJ's Smart Beta Platform (in-house proprietary model of NJAMC). Calculations are for the period 30th September 2006 to 31st December 2024. The Drawdown for a specific date has been calculated by dividing that day's NAV of NJ Quality+ Model, Low Quality Model and Nifty 500 TRI by their peak NAVs up to that date, respectively. Past performance may or may not be sustained in future and is not indication of future return. NJ Quality+ Model and Low Quality Model are proprietary methodologies developed by NJ Asset Management Private Limited. The methodologies will keep evolving with new insight based on the ongoing research and will be updated accordingly from time to time.

2.8 Performance of Select Quality Parameters

At NJ AMC, an exhaustive examination of various quality parameters has been undertaken, revealing several robust metrics indicative of a company's financial robustness. Some of these metrics are Return on Equity (ROE), ROE Consistency, Dividend Payout Ratio, Debt-to-Equity, and Current Ratio Consistency. We would like to share an analysis of the comparative performance between high-quality and low-quality stocks as measured by these metrics. The findings demonstrate that high quality stocks have consistently outperformed their lower-quality counterparts and market indices over extended periods.

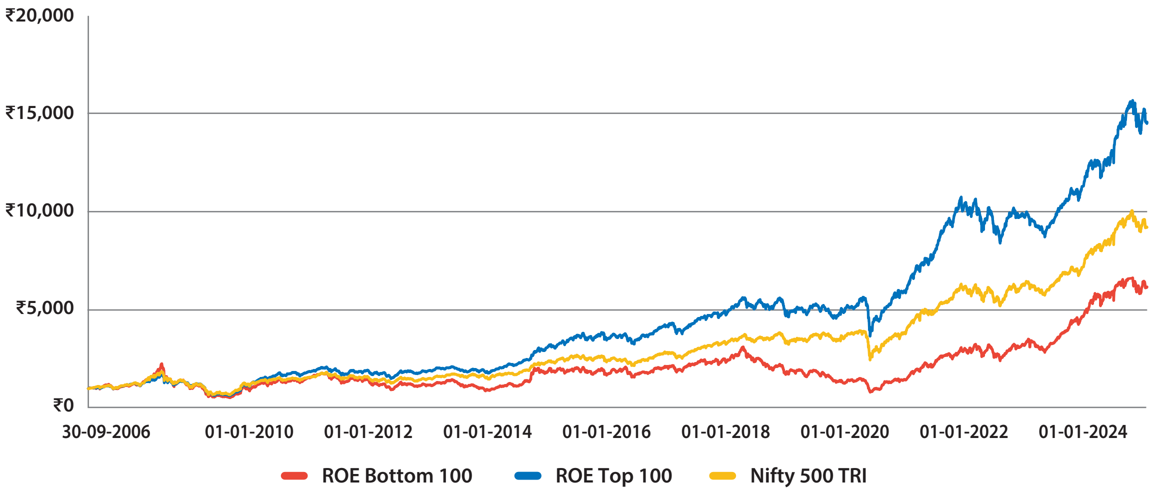
Presented below is the cumulative growth of ₹1000 from September 2006 to December 2024 for both the top 100 high-quality and bottom 100 low-quality stocks, alongside the Nifty 500 Index, for respective quality parameters. The accompanying table displays the Compound Annual Growth Rate (CAGR), annualised volatility, 10-year median Rolling Returns, Maximum Drawdown and Cumulative Growth of ₹1000. It is noteworthy to emphasise the superior risk-adjusted returns attained by high-quality stocks, assessed through diverse quality parameters, in contrast to low-quality stocks and the market index throughout this specified timeframe.

A. Return on Equity

- Return on Equity (ROE) measures how effectively a company generates profits from the equity invested by shareholders. A higher ROE often signifies superior financial performance and management efficiency, making it a valuable metric for assessing quality.
- ROE= (Net Income / Shareholders' Equity) x 100
- Example: If a company has a net income of ₹50 lakhs and shareholders' equity of ₹200 lakhs:
  ROE= (50 / 200)×100= 25%

This means for every ₹1 of equity, the company generates ₹0.25 in profit.

High Vs Low Return on Equity



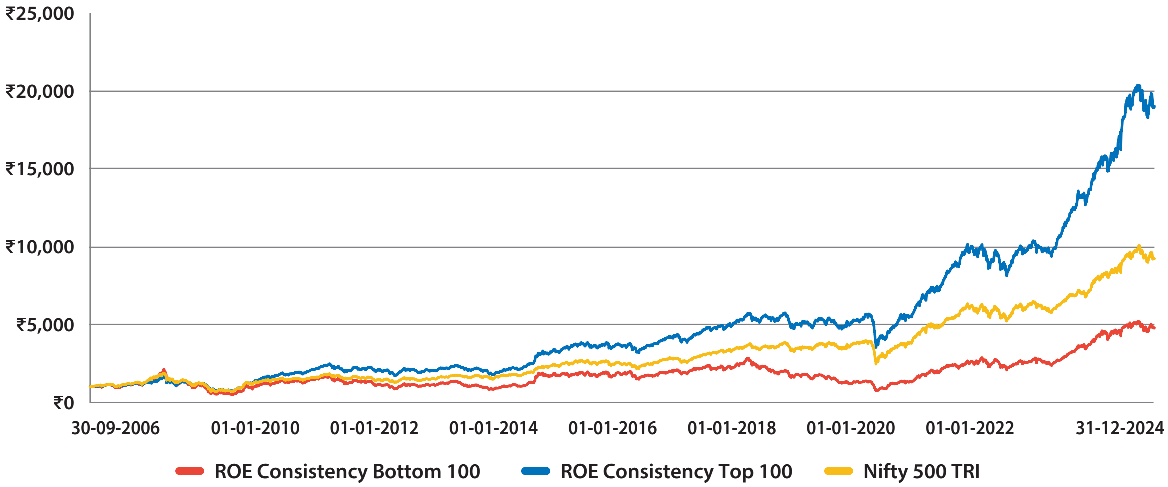
From Sep 2006 to Dec 2024	CAGR (%)	10 Year Median Rolling Returns (%)	Annualised Volatility (%)	Maximum Drawdown (%)	Cumulative Growth of 1000
ROE Top 100	15.80	16.37	17.41	-63.94	₹14,586
ROE Bottom 100	10.49	7.95	24.87	-76.55	₹6,185
Nifty 500 TRI	12.92	13.03	20.18	-63.71	₹9,214

Source: CMIE, NJ's Smart Beta Platform. Data for the period 30th September 2006 to 31st December 2024. Past performance may or may not be sustained in future and is not indication of future return.

B. Return on Equity Consistency

- ROE Consistency highlights how reliably a company maintains its profitability over time, reflecting stability and a strong operational framework. Companies with consistently high ROE are better positioned to weather economic fluctuations, as shown in the graph comparing top performers to bottom firms and the benchmark index, Nifty 500.
- Example: If a company's ROE for the last 5 years is 22%, 23%, 21%, 22.5%, and 23.2%, it shows consistent performance, suggesting stability.

Consistent Vs Inconsistent Return on Equity



From Sep 2006 to Dec 2024	CAGR (%)	10 Year Median Rolling Returns (%)	Annualised Volatility (%)	Maximum Drawdown (%)	Cumulative Growth of 1000
ROE Consistency Top 100	17.50	15.98	17.72	-57.90	₹19,026
ROE Consistency Bottom 100	8.95	7.37	24.79	-77.08	₹4,789
Nifty 500 TRI	12.92	13.03	20.18	-63.71	₹9,214

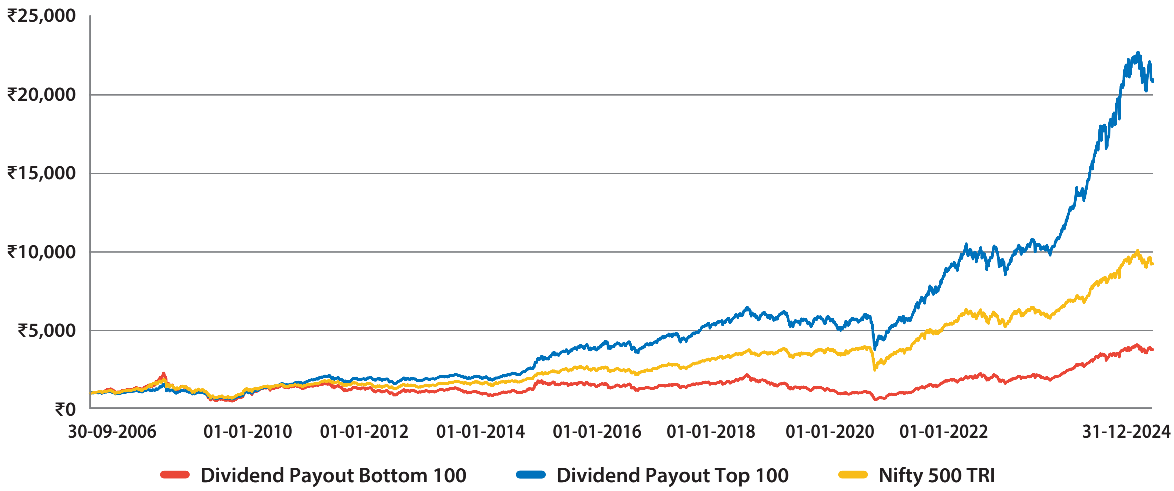
Source: CMIE, NJ's Smart Beta Platform. Data for the period 30th September 2006 to 31st December 2024. Past performance may or may not be sustained in future and is not indication of future return.

C. Dividend Payout

- The Dividend Payout Ratio demonstrates the proportion of earnings distributed as dividends, balancing shareholder returns with retained earnings for growth. Quality companies strike the right balance, rewarding investors while reinvesting strategically. The graph clearly illustrates how top companies outperform compared to their peers.
- Dividend Payout Ratio= (Dividends Paid / Net Income) x 100
- Example: If a company has a net income of ₹40 lakhs and pays ₹10 lakhs as dividends:
  Dividend Payout Ratio= (10 / 40)×100= 25%

This means the company pays out 25% of its profits as dividends.

High Vs Low Dividend Payout



From Sep 2006 to Dec 2024	CAGR (%)	10 Year Median Rolling Returns (%)	Annualised Volatility (%)	Maximum Drawdown (%)	Cumulative Growth of 1000
Dividend Payout Top 100	18.11	17.67	17.13	-60.31	₹20,934
Dividend Payout Bottom 100	7.54	4.16	24.65	-78.38	₹3,775
Nifty 500 TRI	12.92	13.03	20.18	-63.71	₹9,214

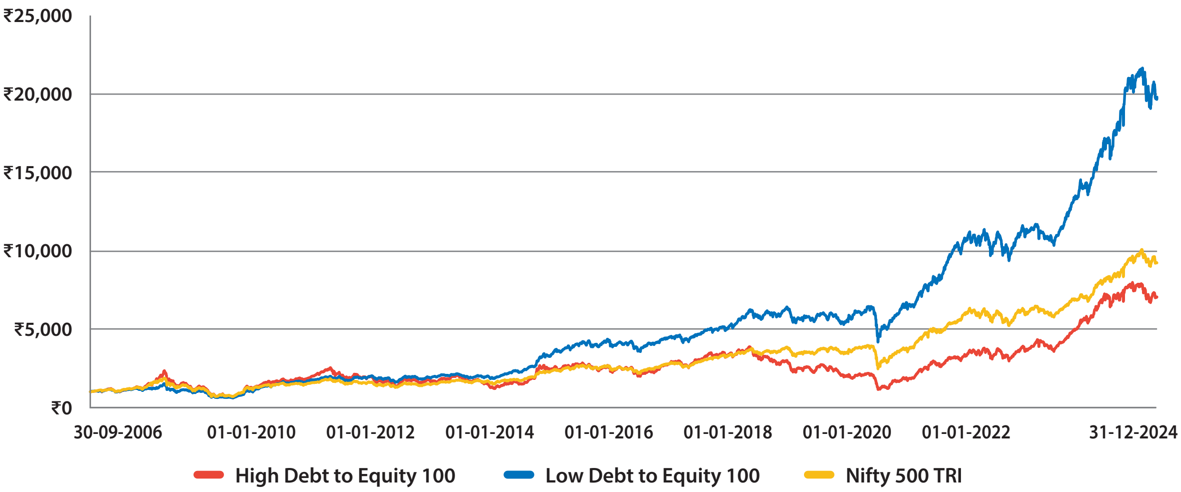
Source: CMIE, NJ's Smart Beta Platform. Data for the period 30th September 2006 to 31st December 2024. Past performance may or may not be sustained in future and is not indication of future return.

D. Debt to Equity

- Debt to Equity Ratio evaluates the level of financial leverage a company employs, showing how effectively it balances debt and equity to fund operations. A low ratio indicates a sound financial structure, while excessive debt can raise risk levels. Companies with low debt levels excel here by maintaining sustainable leverage, as evident in their graph performance relative to weaker firms and the broader market.
- Debt to Equity Ratio= (Total Debt / Shareholders' Equity)
- Example: If a company has total debt of ₹100 lakhs and shareholders equity of ₹50 lakhs:
  Debt to Equity Ratio= (100 / 50)= 2

This means the company uses ₹2 of debt for every ₹1 of equity.

High vs Low Debt to Equity



From Sep 2006 to Dec 2024	CAGR (%)	10 Year Median Rolling Returns (%)	Annualised Volatility (%)	Maximum Drawdown (%)	Cumulative Growth of 1000
Low Debt to Equity 100	17.75	18.39	16.84	-60.49	₹19,794
High Debt to Equity 100	11.27	8.25	24.91	-74.10	₹7,041
Nifty 500 TRI	12.92	13.03	20.18	-63.71	₹9,214

Source: CMIE, NJ's Smart Beta Platform. Data for the period 30th September 2006 to 31st December 2024. Past performance may or may not be sustained in future and is not indication of future return.

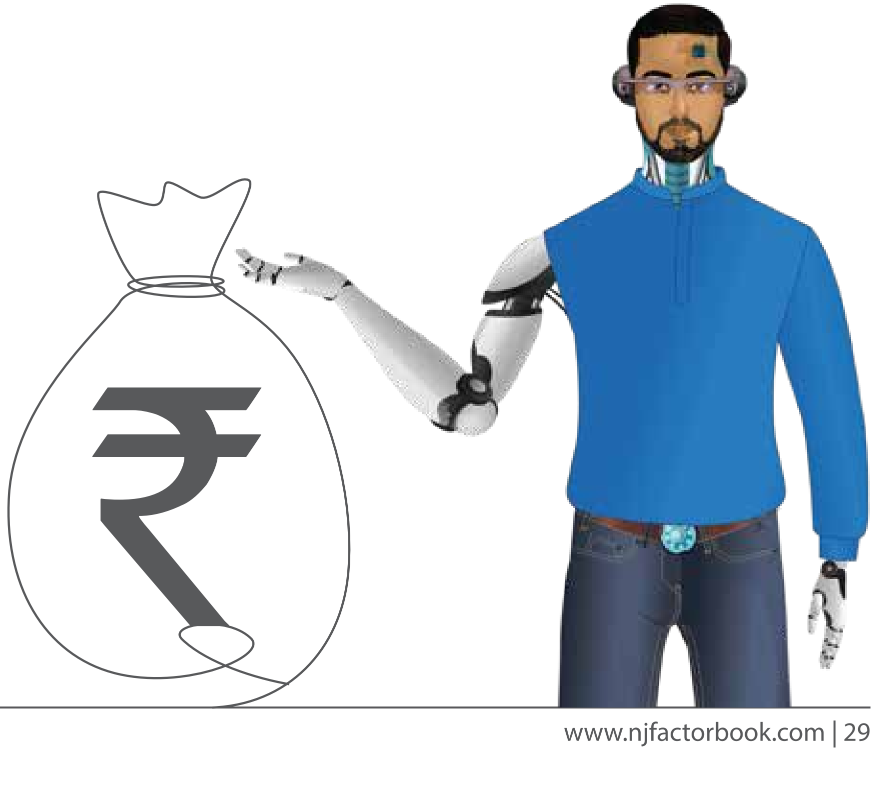
3. Value **Factor**

The secret to investing is to figure out the value of something - and then pay a lot less.

-John Ruskin

I make no attempt to forecast the market-my efforts are devoted to finding undervalued securities.

-Warren Buffett



For More Details

3. Value **Factor**

3.1 What is 'Value' Investing?

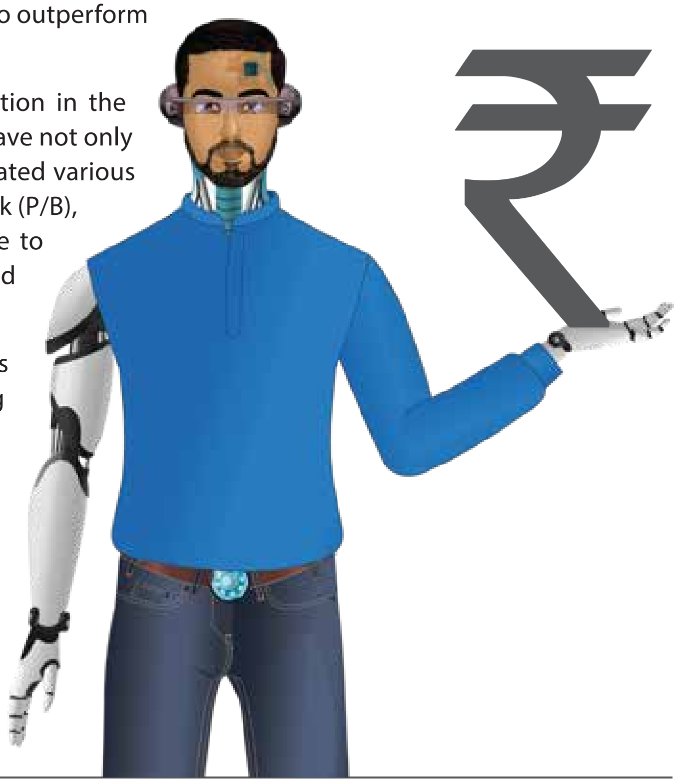
Value investing is a well-regarded investment strategy with its roots tracing back several centuries. However, it was only in the 20th century that it began to crystallise into a formalised approach, with a significant milestone being the publication of "Security Analysis" by Benjamin Graham and David Dodd in the 1930s. This book introduced a method to ascertain a company's intrinsic value based on its Earnings Per Share (EPS) and long-term growth prospects. Graham further refined this approach in his subsequent book "The Intelligent Investor" (1974), though the essence of the strategy remained intact.

The core idea of value investing revolves around the "value factor," which is a fundamental component of factor investing. It posits that stocks priced below their intrinsic value have a higher likelihood of outperforming those priced at a premium over time. This hypothesis is anchored in the assertion that market inefficiencies can result in mispricing, thus creating opportunities for astute value investors to achieve superior returns.

The pivotal research by Eugene Fama and Kenneth French in 1992, titled "The Cross-Section of Expected Stock Returns," lent empirical support to the value factor. Their findings illustrated that portfolios consisting of stocks with low price-to-book (P/B) ratios tended to outperform those with high P/B ratios over an extended period.

Since then, the value factor has attracted considerable attention in the academic realm, fostering a robust body of research. Scholars have not only corroborated the legitimacy of the value factor but also delineated various metrics to gauge it, such as Price-to-Earnings (P/E), Price-to-Book (P/B), Price-to-Sales (P/S), Price-to-Cash Flow (P/CF), Enterprise Value to Earnings Before Interest, Taxes, Depreciation, and Amortized Expenses (EV/EBITDA), and Dividend Yield, among others.

It's noteworthy to mention that while the value factor has showcased its potential to yield superior returns over the long haul, value investing carries its set of risks. Value stocks may display heightened volatility in comparison to growth stocks, and there could be phases where they lag. Hence, investors are advised to understand and carefully navigate the intricacies and trade-offs embedded in the pursuit of value-centric strategies.



3.2 How is 'Value' Measured?

Index providers across the world now publish factor indexes using various definitions of the factors. A simple way to ascertain the most popular definitions of value across the world is to inspect the definitions used by the various index providers for their value indexes. A summary of the same is in the table below.

Index Details	Factor Characteristics	Methodology
Index Name: FTSE Value Factor Index Index Provider: FTSE Russell	Cash flow yield, earnings yield and P/S	Tilt the market capitalisation index by using a composite score
Index Name: MSCI Enhanced Value Index Index Provider: MSCI Inc	Forward P/E, P/B, and Enterprise value to operating cash flow	Tilt the market capitalisation index using the composite score and target a fixed number of stocks, targeting 30% market capitalisation coverage.
Index Name: S&P Enhanced Value Index Index Provider: S&P Dow Jones Indices LLC	P/B, P/E and P/S	Tilt the market capitalisation index by targeting a fixed percentage of constituents in the market capitalisation index.
Index Name: Dow Jones U.S. Large-Cap Value Total Stock Market Index Index Provider: S&P Dow Jones Indices LLC	Projected P/E, Projected 3-5 Yr Operating EPS Growth, P/B, Div Yield, Trailing Revenue Growth (5 Yrs), Trailing EPS Growth (Last 21 quarters)	Tilt the US Large-Cap Total Stock Market Index (float-adjusted capitalisation-weighted) towards its constituents classified as "value" using a 6-factor composite score and cluster analysis.
Index Name: Nifty 500 Value 50 Index Index Provider: NSE Indices Ltd	E/P, B/P, Sales/Price, Dividend Yield	Tilt the Nifty 500 Index (capitalisation-weighted) towards specific constituents based on a weighted-average "Value" score and free-float market capitalisation.

Source: FTSE Russell, MSCI Inc, S&P Dow Jones Indices LLC & NSE Indices Ltd.

3.3 Does the Value Factor work?

The historical performance of value investing has witnessed various phases of outperformance and underperformance in comparison to growth investing, reflecting the cyclical nature of these investment styles. Here's a summarised analysis based on historical data:

Long-Term Performance:

Dating back to 1926 in the US markets, value investing has yielded a return of 1,344,600%, outperforming the S&P 500 which returned 1,256,300% over the same period. This data underscores the long-term potential of value investing, even though it doesn't guarantee future performance (Baldridge, R., & Curry, B. (2022) & Webster, I. (n.d.))

Performance Downturn Post-2007:

Value investing experienced a significant underperformance since 2007. This downturn is noted to be a stark contrast to value's strong long-term returns, indicating a challenging phase for value investing (Weng, J., & Butler, I. (2022)).

Recent Performance Shift:

Since late 2020, there has been a shift where value started to outperform, although this change is considered relatively minor when viewed against the backdrop of value's underperformance since 2007 (Weng, J., & Butler, I. (2022)).

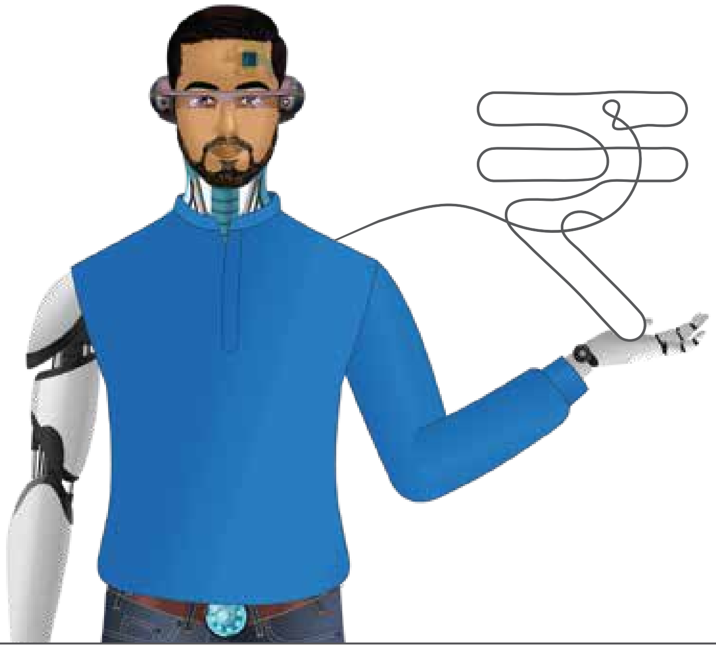
Historical Leadership:

Over the last 30 years, there have been phases of value investing leading and lagging, reflecting the cyclical nature of this style and the influence of broader market and economic conditions on their performance (Bischof, B. (2021)).

The historical data showcases the cyclical performance trends of value investing. While value investing has shown strong returns over the long run, there have been extended periods, such as post-2007, where it lagged behind markets. These insights underline a blend of macroeconomic and market-specific factors impacting the performance and perception of value investing.

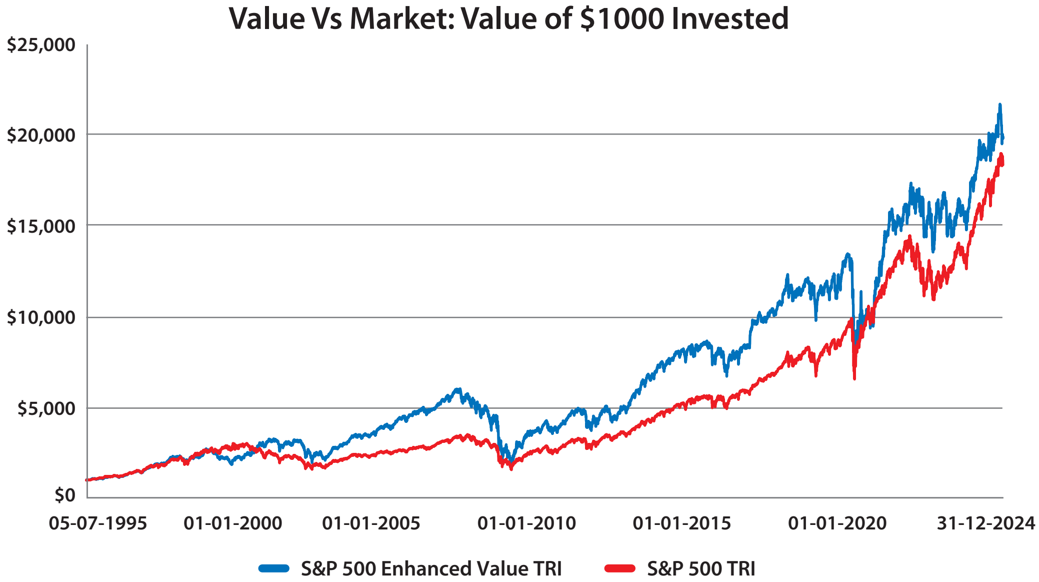
While the traditional principles of value investing remain valid, the evolving market dynamics and external factors like the pandemic have imposed challenges and necessitated a more nuanced approach to value investing. The situation in India, as noted, presents additional complexities due to the presence of "value traps" and perpetual value companies affecting the overall performance of the value factor in the Indian market. Nonetheless, the low correlation of the value factor with quality, momentum and other factors offers diversification benefits, hinting at the enduring relevance of value investing in diversified investment strategies.

This has encouraged us to look beyond the traditional measures of value and return to incorporating growth when calculating the intrinsic value of a stock as originally envisaged by Benjamin Graham and David Dodd.

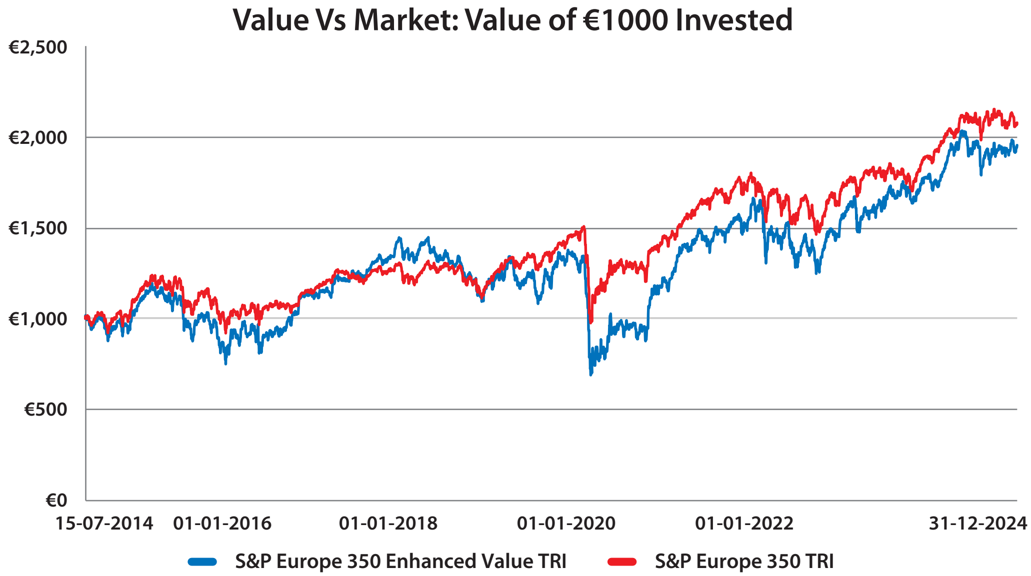


3.4 Performance of Value Factor Across Markets: USA, Europe, and India

The analysis of the Value factor across the USA, Europe, and India provides insights into its long-term performance trends and cyclicality. The line graphs illustrate the relative growth of the Value indices against their benchmarks, while the tables highlight period-wise performance trends over different market cycles.



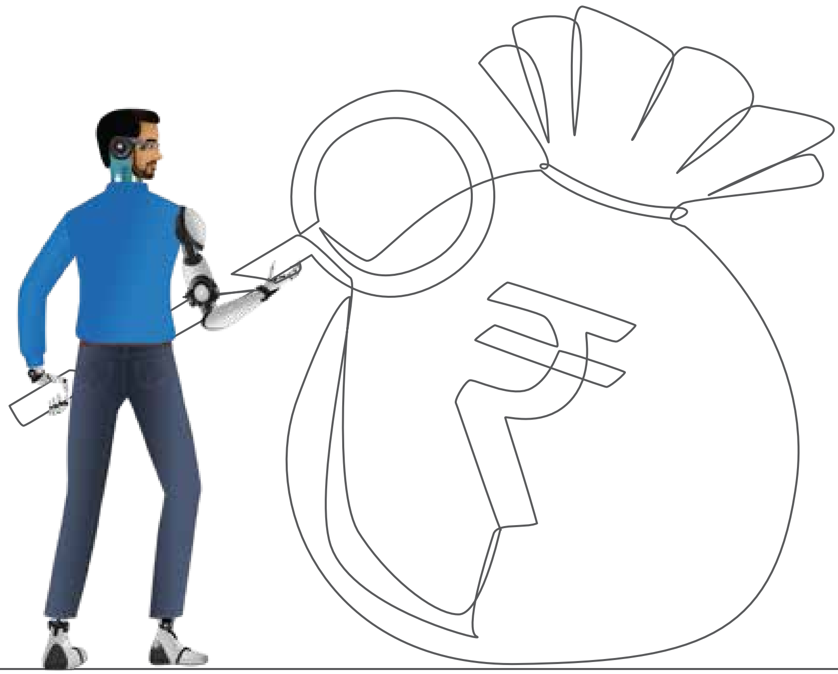
Source : Bloomberg. This chart depicts the growth in the NAV of S&P 500 Enhanced Value TRI vis-a-vis that of the S&P 500 TRI over the period 5th July 1995 to 31st December 2024. All the NAVs are in USD and have not been converted to INR. All the indices have been scaled to $1,000 as of 5th July 1995. Past performance may or may not be sustained in future and is not an indication of future return.



Source : Bloomberg. This chart depicts the growth in the NAV of S&P Europe 350 Enhanced Value TRI vis-a-vis that of the S&P Europe 350 TRI over the period 15th July 2014 to 31st December 2024. All the NAVs are in EUR and have not been converted to INR. All the indices have been scaled to €1,000 as of 15th July 2014. Past performance may or may not be sustained in future and is not an indication of future return.

Value Vs Market: Value of ₹1000 Invested

Source : NSE. This chart depicts the growth in the NAVs of Nifty 500 Value 50 TRI vis-a-vis that of the Nifty 500 TRI over the period 1st April 2005 to 31st December 2024. All the indices have been scaled to ₹1,000 as of 1st April 2005. Past performance may or may not be sustained in future and is not an indication of future return.



Period-wise Summary of Factor Performance: Value Vs Market

Region	Period	Annualised Return (%)		3-Year Median Rolling Return (%)		10-Year Median Rolling Return (%)	
		Value	Market	Value	Market	Value	Market
USA	Jul 5, 1995 - Dec 31, 2000	19.82	19.32	21.12	25.80	-	-
	Jan 1, 2001 - Dec 31, 2006	12.27	2.94	14.49	8.98	-	-
	Jan 1, 2007 - Dec 31, 2012	-0.61	2.29	0.10	1.58	-	-
	Jan 1, 2013 - Dec 31, 2018	12.10	12.15	9.59	10.90	-	-
	Jan 1, 2019 - Dec 31, 2024	11.47	16.95	10.39	10.35	-	-
	Entire Period	10.66	10.36	10.53	11.20	8.76	7.98
Europe	Jul 15, 2014 - Dec 31, 2018	2.54	2.97	7.87	3.61	-	-
	Jan 1, 2019 - Dec 31, 2024	9.77	10.55	10.01	8.99	-	-
	Entire Period	6.62	7.25	7.66	7.60	7.03	7.60
India	Apr 1, 2005 - Dec 31, 2012	16.52	14.79	22.36	8.58	-	-
	Jan 1, 2013 - Dec 31, 2018	11.32	12.75	18.33	13.11	-	-
	Jan 1, 2019 - Dec 31, 2024	23.32	17.20	39.37	19.28	-	-
	Entire Period	17.03	14.96	16.12	13.11	14.08	12.75

Source : Bloomberg, NSE. Past performance may or may not be sustained in future and is not an indication of future return.The S&P 500 Enhanced Value TRI, S&P Europe 350 Enhanced Value TRI, & Nifty 500 Value 50 TRI are used to represent the Value index for the USA, Europe and India regions respectively. The S&P 500 TRI, S&P Europe 350 TRI, & Nifty 500 TRI are used to represent the market index for the USA, Europe and India regions respectively.

3.5 NJ's Value Factor - NJ Traditional Value & NJ Enhanced Value Models

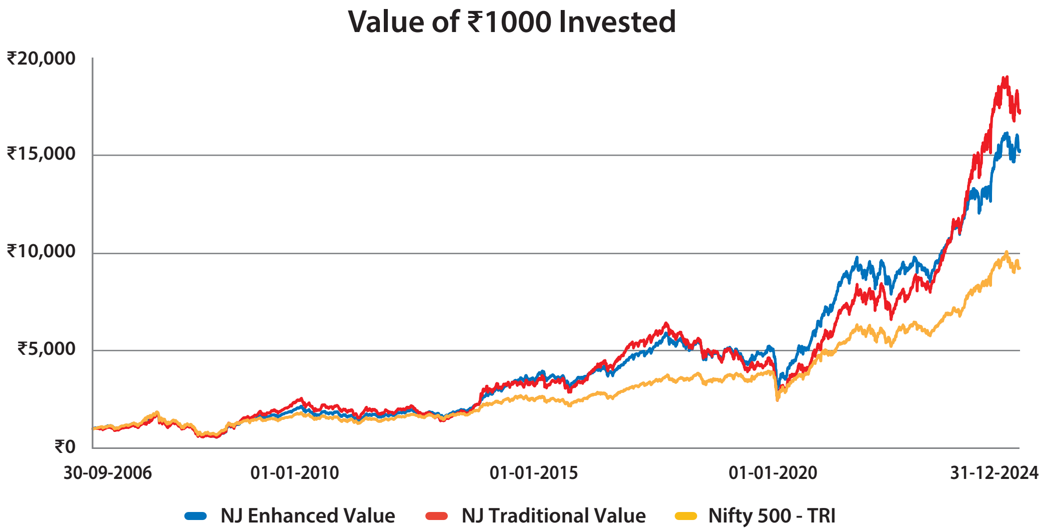
A combination of good value parameters, portfolio diversification, and a robust weighting approach can assist in capturing the value factor to a large extent.

NJ Asset Management's research shows that value characteristics are cyclical and may perform differently for different sectors. In addition, there are important differences in how value needs to be measured for financial and non-financial companies. There is also the additional challenge of avoiding value traps.

We've developed two distinct value indices: one adheres to the traditional relative value concept, while the other is an enhanced version that employs intrinsic value to categorise value stocks within the universe. To further advance our approach, we have refined both methodologies, incorporating deeper valuation insights to improve stock selection.

The NJ Enhanced Value model adopts a Discounted Cash Flow (DCF) approach to estimate the intrinsic value of companies and identify potential mispricing. By assessing whether a stock is trading below its intrinsic worth, this methodology seeks to identify and leverage undervalued opportunities. The model selects the Top 100 Value stocks from the Nifty 500 universe, maintaining an equal-weighted portfolio.

The NJ Traditional Value model incorporates a broader range of valuation factors to assess a stock's relative valuation. It evaluates companies based on Earnings to Price (EP), relative valuation through the ratio of Average 5-Year PE to Current PE, Free Cash Flow to Firm (FCFF) relative to Enterprise Value (EV), Book Value to Price, Forecasted EPS Growth in relation to PE, and Dividend Yield. By incorporating multiple valuation metrics, this methodology enhances the ability to identify fundamentally strong value stocks. The model selects the Top 100 Value stocks from the Nifty 500 universe with an equal-weighted portfolio.



Source: Internal research, Bloomberg, CMIE, National Stock Exchange, NJ's Smart Beta Platform (in-house proprietary model of NJAMC). Calculations are for the period 30th September 2006 to 31st December 2024. NJ Traditional Value Model and NJ Enhanced Value Model are in-house proprietary methodologies developed by NJ Asset Management Private Limited. The methodologies will keep evolving with new insight based on the ongoing research and will be updated accordingly from time to time.
Past performance may or may not be sustained in future and is not an indication of future return. The above is only for illustration purposes and should not be construed as indicative return of offering of NJ Asset Management Private Limited.

The models display the following characteristics vis-a-vis the benchmark Nifty 500 TRI.

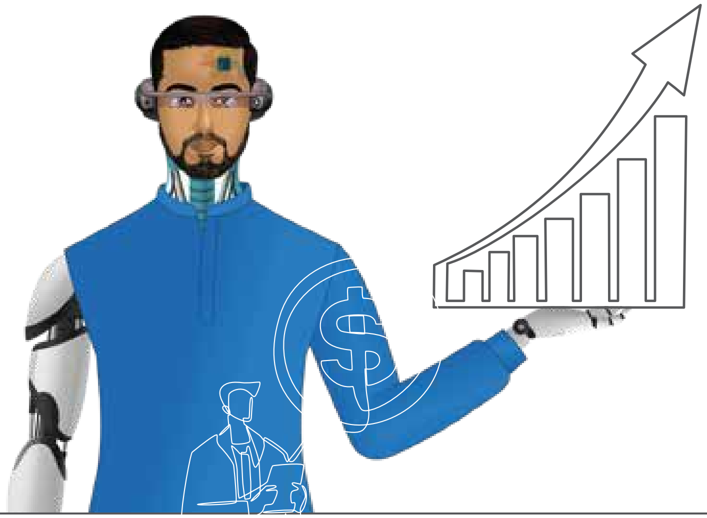
	P/E	Dividend Yield	EV to EBIT	P/BV
NJ Enhanced Value	26.59	0.37	26.86	4.97
NJ Traditional Value	18.05	1.31	20.42	2.84
Nifty 500 TRI	25.56	1.12	32.27	3.88

Source : Internal research, CMIE, National Stock Exchange of India, NJ's Smart Beta Platform (in-house proprietary model of NJAMC). Factor parameters calculated as on 31st December 2024. For Nifty 500 TRI, the data for P/E, Dividend Yield and P/BV is taken from the official website of the National Stock Exchange of India. NJ Traditional Value Model and NJ Enhanced Value Model factor definition are the weighted harmonic mean of its constituents. Past performance may or may not be sustained in future and is not an indication of future return. Outliers are not considered while calculating the numbers. Companies with negative EBIT and lending companies are not considered for EV to EBIT. NJ Traditional Value Model and NJ Enhanced Value Model are proprietary methodologies developed by NJ Asset Management Private Limited. The methodologies will keep evolving with new insight based on the ongoing research and will be updated accordingly from time to time.

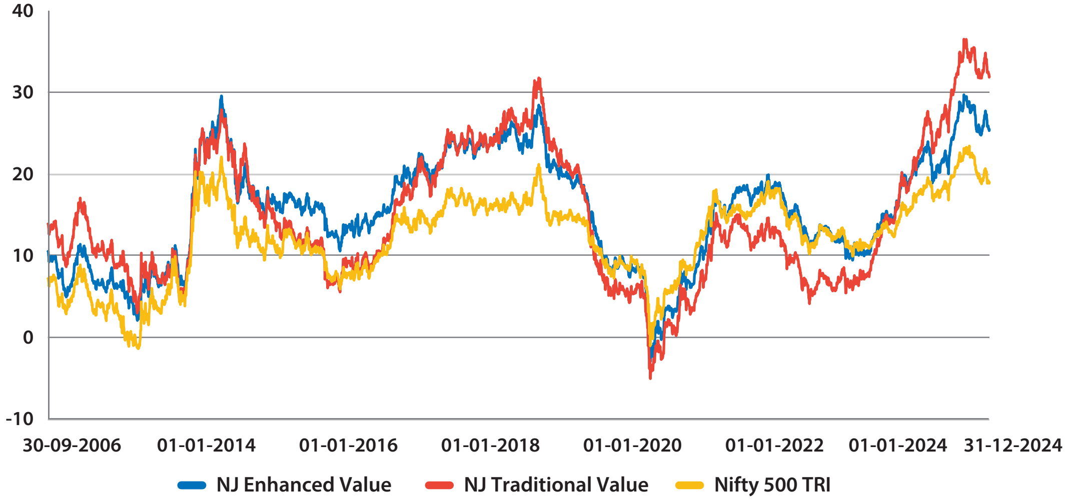
Period-wise Performance of NJ Value Portfolios and Nifty 500 TRI

Period	NJ Enhanced Value (%)	NJ Traditional Value (%)	Nifty 500 TRI (%)
Sep 30, 2006 - Dec 31, 2012	11.18	12.64	8.95
Jan 1, 2013 - Dec 31, 2018	16.57	15.15	12.75
Jan 1, 2019 - Dec 31, 2024	20.77	23.03	17.20
Entire Period	16.09	16.89	12.92

Source : Internal research, CMIE, National Stock Exchange, NJ's Smart Beta Platform (in-house proprietary model of NJAMC). Return calculations are based on CAGR (Compound Annual Growth Rate) for each period. NJ Traditional Value Model and NJ Enhanced Value Model are in-house proprietary methodologies developed by NJ Asset Management Private Limited. The methodologies will keep evolving with new insight based on the ongoing research and will be updated accordingly from time to time. Past performance may or may not be sustained in future and is not an indication of future return. The above is only for illustration purposes and should not be construed as indicative return of offering of NJ Asset Management Private Limited.

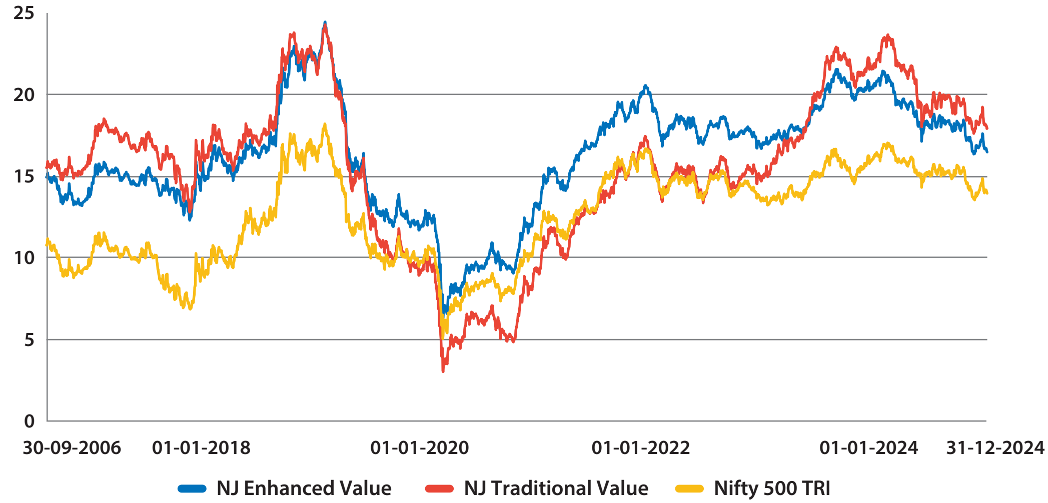


NJ Enhanced Value, NJ Traditional Value vs Nifty 500 TRI : 5-Yr Rolling Returns



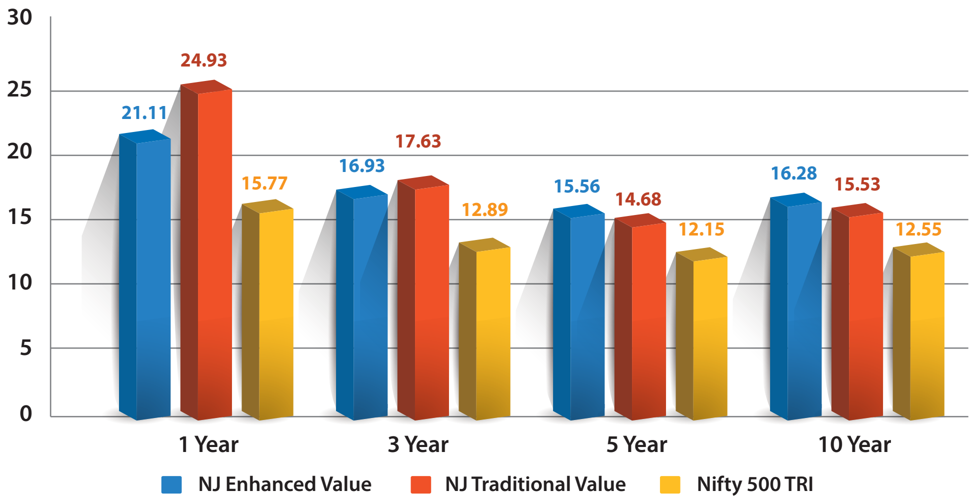
Source : Internal research, Bloomberg, CMIE, National Stock Exchange of India, NJ's Smart Beta Platform (in-house proprietary model of NJAMC). 5-Yr CAGRs are calculated for the period 30th September 2006 to 31st December 2024 and have been rolled on a daily basis. Past performance may or may not be sustained in future and is not indication of future return. NJ Enhanced Value Model and NJ Traditional Value Model are proprietary methodologies developed by NJ Asset Management Private Limited. The methodologies will keep evolving with new insight based on the ongoing research and will be updated accordingly from time to time.

NJ Enhanced Value, NJ Traditional Value vs Nifty 500 TRI : 10-Yr Rolling Returns



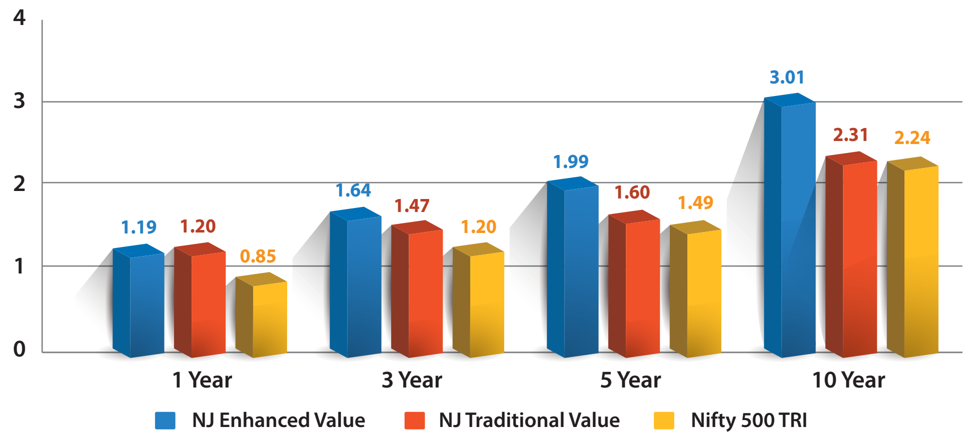
Source : Internal research, Bloomberg, CMIE, National Stock Exchange of India, NJ's Smart Beta Platform (in-house proprietary model of NJAMC). 10-Yr CAGRs are calculated for the period 30th September 2006 to 31st December 2024 and have been rolled on a daily basis. Past performance may or may not be sustained in future and is not indication of future return. NJ Enhanced Value Model and NJ Traditional Value Model are proprietary methodologies developed by NJ Asset Management Private Limited. The methodologies will keep evolving with new insight based on the ongoing research and will be updated accordingly from time to time.

NJ Value vs Nifty 500 TRI : Average Rolling CAGR



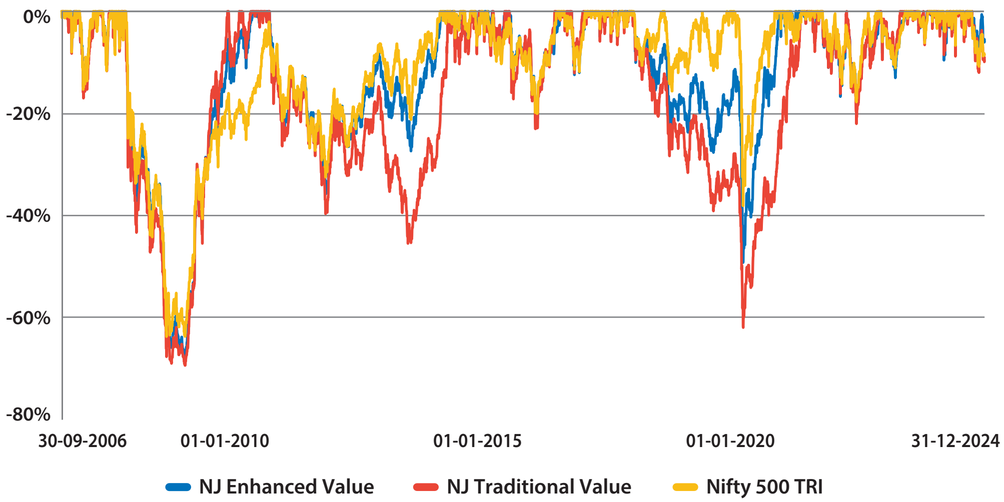
Source: Internal research, Bloomberg, CMIE, National Stock Exchange of India. CAGRs are calculated as the average CAGR based on the rolling CAGRs (rolled daily) calculated for the respective holding periods i.e. 1, 3, 5, and 10-Yr rolling CAGRs. The period for calculation is 30th September 2006 to 31st December 2024. Past performance may or may not be sustained in future and is not an indication of future return. NJ Traditional Value Model & NJ Enhanced Value Model are proprietary methodologies developed by NJ Asset Management Private Limited. The methodologies will keep evolving with new insight based on the ongoing research and will be updated accordingly from time to time.

NJ Value vs Nifty 500 TRI : Return / Standard Deviation



Source: Internal research, Bloomberg, CMIE, National Stock Exchange of India. The Return/Standard Deviation ratios have been calculated by dividing the respective rolling returns (rolled daily) by the standard deviation of the corresponding rolling returns, calculated over the period 30th September 2006 to 31st December 2024. Past performance may or may not be sustained in future and is not an indication of future return. NJ Traditional Value Model and NJ Enhanced Value Model are proprietary methodology developed by NJ Asset Management Private Limited. The methodologies will keep evolving with new insights based on the ongoing research and will be updated accordingly from time to time.

NJ Enhanced Value, NJ Traditional Value vs Nifty 500 TRI : Maximum Drawdown



	NJ Enhanced Value	NJ Traditional Value	Nifty 500 TRI
Maximum Drawdown	**-68.34%**	**-69.35%**	**-63.71%**

Source: Internal research, Bloomberg, CMIE, National Stock Exchange of India, NJ's Smart Beta Platform (in-house proprietary model of NJAMC). Calculations are for the period 30th September 2006 to 31st December 2024. The Drawdown for a specific date has been calculated by dividing that day's NAV of NJ Enhanced Value Model, NJ Traditional Value and Nifty 500 TRI by their peak NAVs up to that date, respectively. Past performance may or may not be sustained in future and is not an indication of future return. NJ Enhanced Value Model and NJ Traditional Value Model are proprietary methodologies developed by NJ Asset Management Private Limited. The methodologies will keep evolving with new insight based on the ongoing research and will be updated accordingly from time to time.

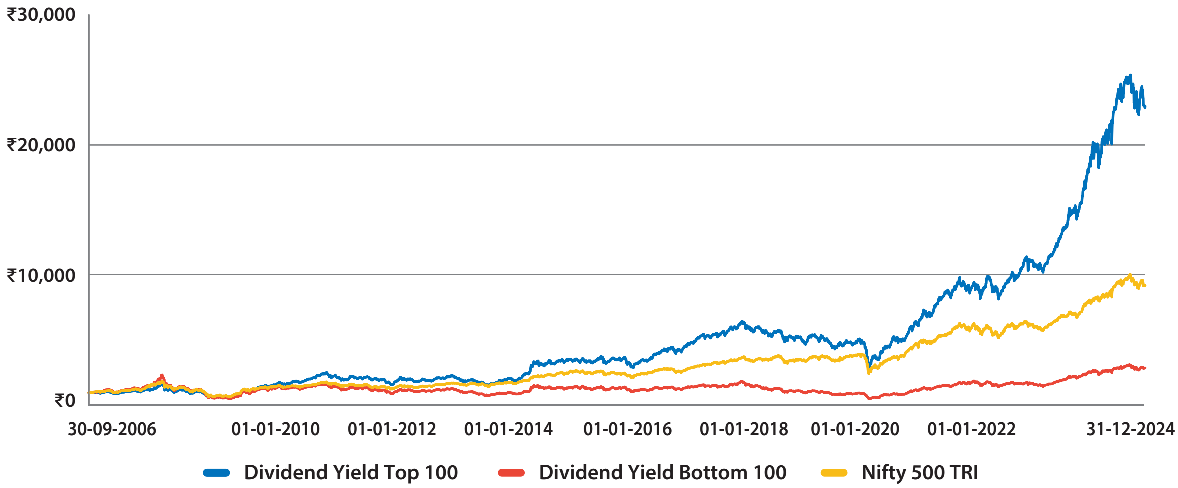
3.6 Performance of Select Value Parameters

A. Dividend Yield

- Dividend Yield is calculated by taking the Trailing Twelve Months (TTM) Dividend Paid and dividing it by the closing price of the stock. This financial ratio provides investors with an indication of the annual dividends paid relative to the market value of the stock.
- Example:
  TTM Dividend Paid: ₹15 per share (Trailing Twelve Months - sum of the last four quarterly dividends)
  Closing Price: ₹1200 per share
- Calculation:
  Dividend Yield = (TTM Dividend Paid / Closing Price) * 100%
  Dividend Yield = (₹15 / ₹1200) * 100%
  Dividend Yield = 1.25%

This means that for every ₹100 invested in the stock, the investor earns an income of ₹1.25 annually in the form of dividends.

High Vs Low Dividend Yield



From Sep 2006 to Dec 2024	CAGR (%)	10 Year Median Rolling Returns (%)	Annualised Volatility (%)	Maximum Drawdown (%)	Cumulative Growth of 1000
Dividend Yield Top 100	18.72	17.11	20.76	-67.08	₹22,975
Dividend Yield Bottom 100	6.00	2.77	24.06	-77.75	₹2,900
Nifty 500 TRI	12.92	13.03	20.18	-63.71	₹9,214

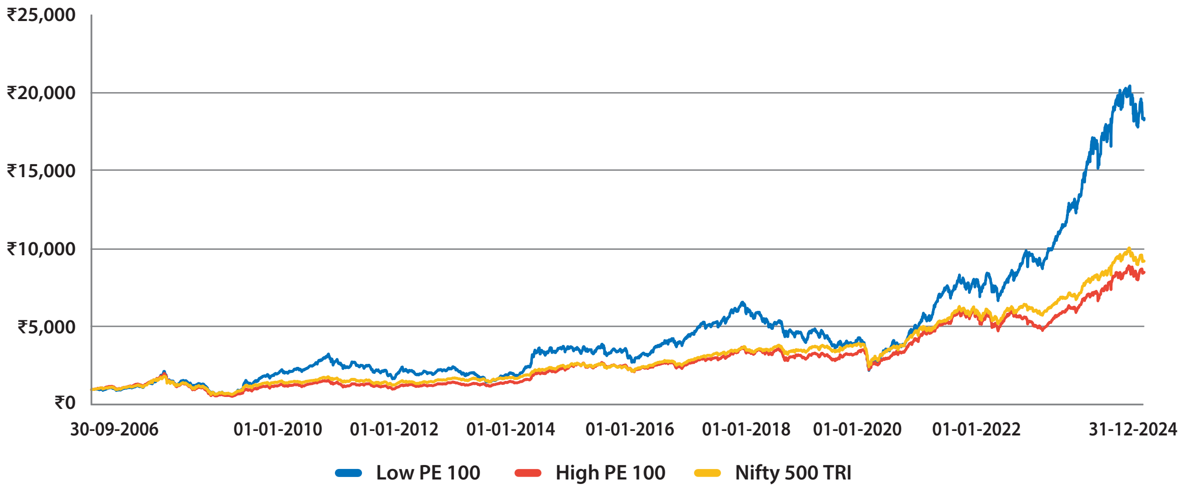
Source: CMIE, NJ's Smart Beta Platform. Data is for the period 30th September 2006 to 31st December 2024. Past performance may or may not be sustained in future and is not indication of future return.

B. Price-to-Earnings (P/E)

- This ratio is calculated by dividing the current market price of a stock by its Earnings Per Share (EPS). This financial ratio helps investors evaluate the relative valuation of a stock by comparing the price investors are willing to pay for each unit of earnings generated by the company. The P/E ratio can be calculated either by using trailing earnings i.e. historical earnings or by using forward or forecasted earnings based on the investors' expectations.
- Example:
  Market Price per Share: ₹1200
  Earnings Per Share (EPS): ₹80
- Calculation:
  P/E Ratio = Market Price per Share / EPS
  P/E Ratio = ₹1200 / ₹80
  P/E Ratio = 15

A P/E ratio of 15 means that investors are willing to pay ₹15 for every ₹1 of the company's earnings.

High Vs Low Price-to-Earnings



From Sep 2006 to Dec 2024	CAGR (%)	10 Year Median Rolling Returns (%)	Annualised Volatility (%)	Maximum Drawdown (%)	Cumulative Growth of 1000
Low Price to Earnings 100	17.27	14.79	23.67	-69.68	₹18,369
High Price to Earnings 100	12.44	13.85	19.37	-72.30	₹8,514
Nifty 500 TRI	12.92	13.03	20.18	-63.71	₹9,214

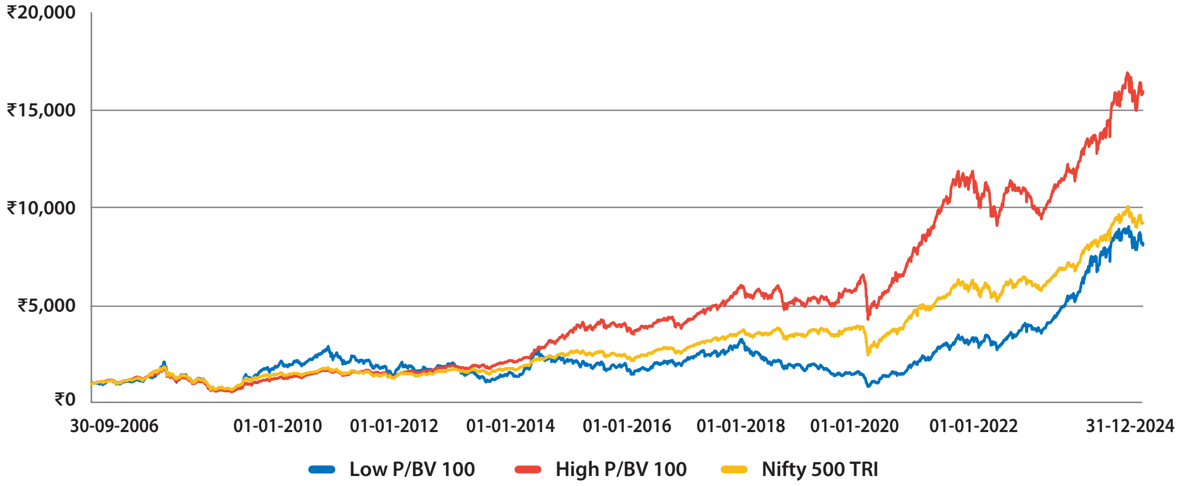
Source: CMIE, NJ's Smart Beta Platform. Data is for the period 30th September 2006 to 31st December 2024. Companies with negative earnings are not considered. Past performance may or may not be sustained in future and is not indication of future return.

C. Price-to-Book Value (P/BV)

- This ratio is calculated by dividing the current market price of a stock by its book value per share i.e. the value of its shareholders equity or net assets. The P/BV ratio helps investors determine whether a stock is overvalued or undervalued compared to the company's net assets.
- Example:
  Market Price per Share: ₹500
  Book Value per Share: ₹250
- Calculation:
  P/BV Ratio = Market Price per Share / Book Value per Share
  P/BV Ratio = ₹500 / ₹250
  P/BV Ratio = 2

A P/BV ratio of 2 indicates that investors are willing to pay ₹2 for every ₹1 of the company's net assets.

High Vs Low Price-to-Book Value



From Sep 2006 to Dec 2024	CAGR (%)	10 Year Median Rolling Returns (%)	Annualised Volatility (%)	Maximum Drawdown (%)	Cumulative Growth of 1000
Low Price to Book Value 100	12.18	6.87	25.75	-74.39	₹8,162
High Price to Book Value 100	16.37	18.41	17.35	-67.87	₹15,954
Nifty 500 TRI	12.92	13.03	20.18	-63.71	₹9,214

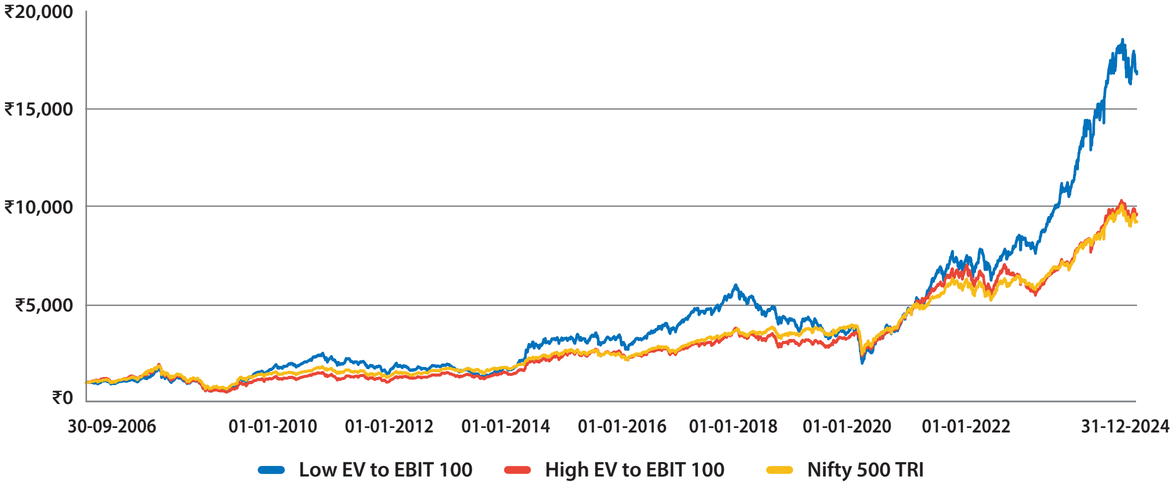
Source: CMIE, NJ's Smart Beta Platform. Data is for the period 30th September 2006 to 31st December 2024. Companies with negative book value are not considered. Past performance may or may not be sustained in future and is not indication of future return.

D. Enterprise Value / Earnings Before Interest and Taxes (EV/EBIT)

- The EV/EBIT ratio is calculated by dividing the enterprise value (EV) of a company by its earnings before interest and taxes (EBIT). This ratio is used to assess a company's valuation while considering both equity and debt.
- Example:
  Enterprise Value (EV): ₹2,40,000 crores
  Earnings Before Interest and Taxes (EBIT): ₹30,000 crores
- Calculation:
  EV/EBIT = Enterprise Value / Earnings Before Interest and Taxes
  EV/EBIT = ₹2,40,000 crores / ₹30,000 crores
  EV/EBIT = 8

An EV/EBIT ratio of 8 means that investors are willing to pay ₹8 for every ₹1 of the company's operating earnings before interest and taxes.

High Vs Low Enterprise Value-to-Earnings Before Interest & Tax



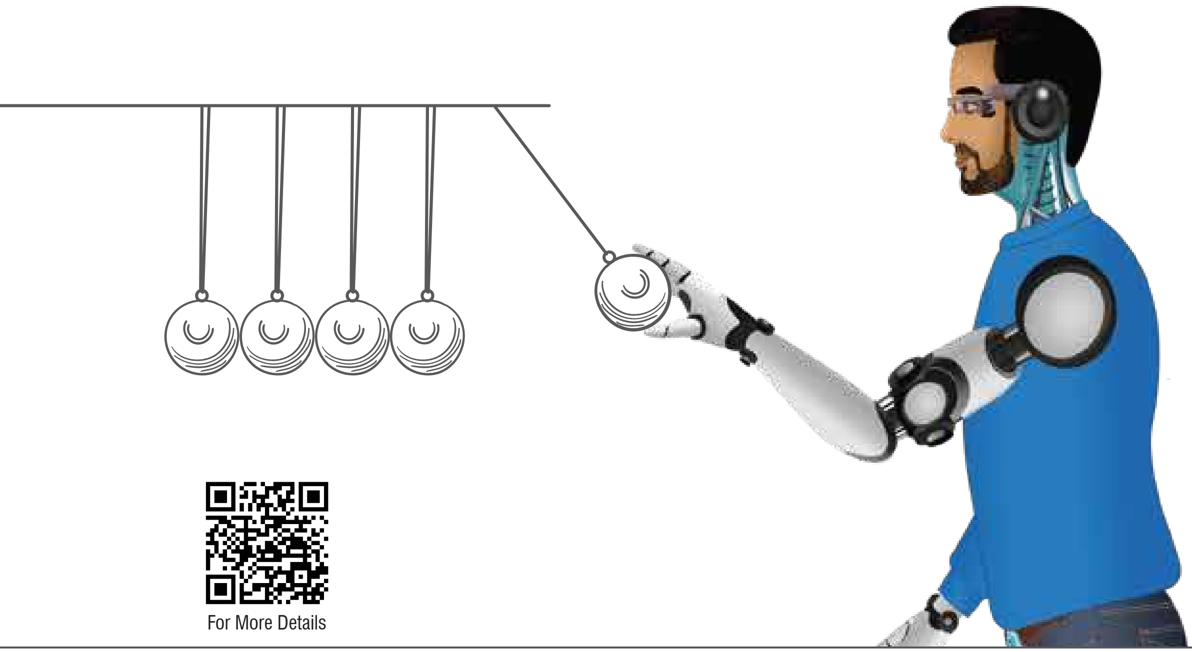
From Sep 2006 to Dec 2024	CAGR (%)	10 Year Median Rolling Returns (%)	Annualised Volatility (%)	Maximum Drawdown (%)	Cumulative Growth of 1000
Low EV to EBIT 100	16.74	15.48	22.26	-69.98	₹16,895
High EV to EBIT 100	13.19	15.25	19.70	-73.44	₹9,623
Nifty 500 TRI	12.92	13.03	20.18	-63.71	₹9,214

Source: CMIE, NJ's Smart Beta Platform. Data is for the period 30th September 2006 to 31st December 2024. Companies with negative EBIT and lending companies are not considered. Past performance may or may not be sustained in future and is not indication of future return.

4. Momentum **Factor**

Momentum solves 80% of your problems.
-John C. Maxwell

Perhaps the best-known
investment paradigm is buy low, sell high.
I believe that more money can be made by buying
high and selling at even higher prices.
-Richard Driehaus



For More Details

4. Momentum **Factor**

4.1 What is 'Momentum' Investing?

Why are runners unable to stop right after crossing the finish line? The force that is applied to move them towards the finish line builds momentum and keeps them moving in the same direction for some time even after the force ceases, which is explained by Newton's first law of motion. Momentum is a vector quantity, containing both speed and direction.

This phenomenon is quite prevalent in the stock market as well with the motion of stocks in response to a sustained force (buying or selling) building momentum. This momentum doesn't stop when the original force wanes but continues to push the stock price in the same direction for some time. In other words, the momentum effect is the propensity of already rising (or falling) securities to continue rising (or falling).

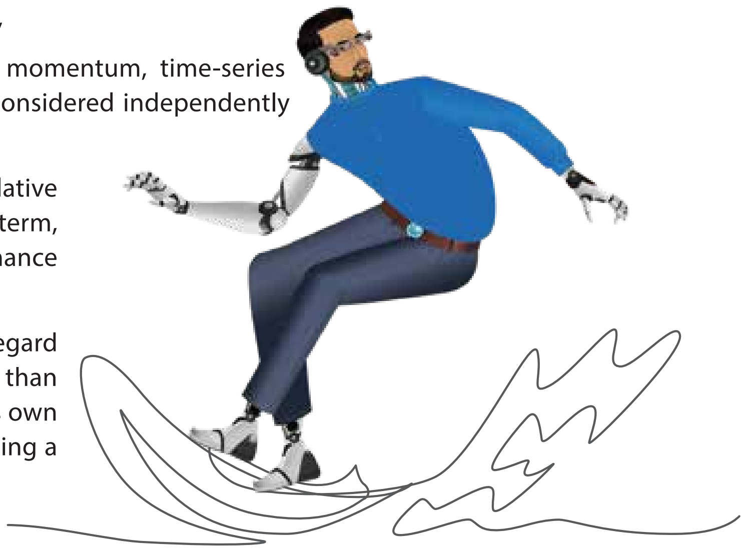
According to the efficient market hypothesis (EMH), momentum premium cannot exist. But momentum effects are pervasive in financial markets. In fact, it is so pervasive that even the Nobel Laureate Eugene Fama, the creator of the EMH, famously said that momentum is "the premier market anomaly". An anomaly is a phenomenon that cannot be explained with theories and that defies rational markets.

Prevalence of irrationalities and behavioural biases such as optimism/pessimism, confirmation bias, representativeness, and herding further boost momentum effect in the markets. Although juxtaposed against popular contrarian strategies such as value investing, momentum has been empirically proven to generate abnormal incremental returns. However, momentum is more of a short-term phenomenon and its return-enhancing effect reduces sharply with time. As a result, using momentum may require frequent rebalancing with the associated increase in portfolio turnover and transaction costs.

There are two momentum approaches in factor investing. These are,

- Time-series momentum: Sometimes referred to as absolute momentum, time-series momentum is calculated based on a stocks own past return, considered independently from the returns of the other stocks.
- Cross-sectional momentum: Originally referred to as relative strength, before academics developed a more jargon-like term, cross-sectional momentum is a measure of a stock's performance relative to other stocks.

Within these two as well, there are many choices to be made with regard to the time period for evaluating momentum, whether to use more than one time period to ascertain change in momentum etc. Each has its own benefits and sacrifices which make this choice a crucial one in crafting a stock selection methodology.



4.2 How is 'Momentum' measured?

There is an abundance of methodologies implemented for momentum strategies. The table below provides an overview of common momentum factor indices among index providers and professionals.

Index Details	Factor Characteristics	Methodology
Index Name: S&P 500 Momentum Index (US) Index Provider: S&P Dow Jones Indices LLC	12-month price change excluding current month (9-month price change if 12-month data unavailable)	Tilt S&P 500 Index (capitalisation- weighted) towards its constituents with weights equal to the product of their market capitalisation weights in Parent Index and Momentum Z-Score
Index Name: MSCI India Momentum Index Index Provider: MSCI Inc.	Risk-adjusted Price Momentum (6-month and 12-month) = [(6/12-month Price Return - Local Risk-free Rate)/SD of returns]	Tilt MSCI India Index (capitalisation-weighted) towards securities based on their Momentum Z-scores with weights equal to the product of Momentum Z-scores and their market capitalisation weights in the Parent Index
Index Name: Nasdaq Factor Family US Momentum Index Index Provider: Nasdaq, Inc.	Momentum Strength Score = Sigma (Ret1,Ret3, Ret6, Ret9, Ret12)/5	50 securities with lowest Adjusted Momentum Strength Score are selected from the eligible universe, subject to a set of constraints
Index Name: Nifty 200 Momentum 30 Index Index Provider: NSE Indices Ltd	6 and 12-month Momentum Ratio (excluding rebalancing month prices) = 6/12-month Price Return/(Ann. SD of lognormal daily returns of the stock for 1 year)	Select top 30 stocks from Nifty 200 (capitalisation-weighted) based on their Normalised Momentum Z-scores. Security weights equal the product of their free-float market capitalisation and Normalised Momentum Score

Source: FTSE Russell, MSCI Inc, S&P Dow Jones Indices LLC, NSE Indices Ltd & Nasdaq, Inc.

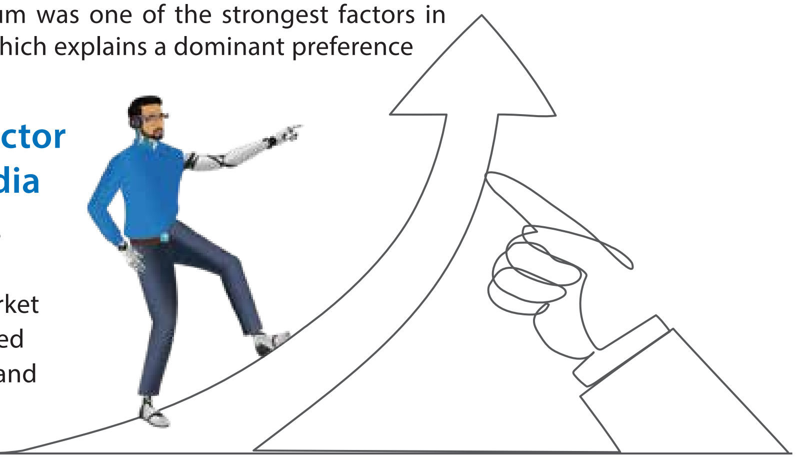
4.3 Does the Momentum Factor work?

The momentum factor has empirically generated positive excess returns, as evidenced by several seminal works including the ones by Jegadeesh and Titman (Jegadeesh & Titman, 1993) and Carhart's 4 Factor Model (Carhart, 1997).

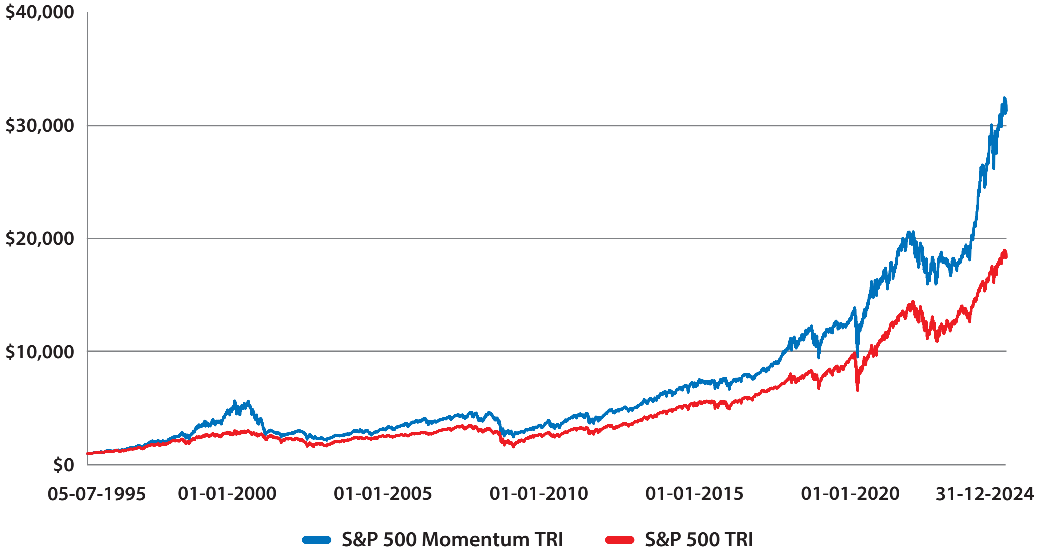
A 2013 study by Professors Agarwalla, Jacob and Varma of the Indian Institute of Management, Ahmedabad (Agarwalla et al., 2013) calculated factor returns for the three Fama French factors and momentum for the Indian stock markets. Covering two decades of data, this study indicates that momentum was one of the strongest factors in India. This is in line with market experience as well which explains a dominant preference for momentum investing.

4.4 Performance of Momentum Factor Across Markets: USA, Europe, and India

The performance of the momentum factor across the USA, Europe, and India highlights its effectiveness in capturing trends and outperforming the broader market over time. The graphs highlight that momentum-based investing has historically added value by identifying and capitalizing on stocks with strong price trends.

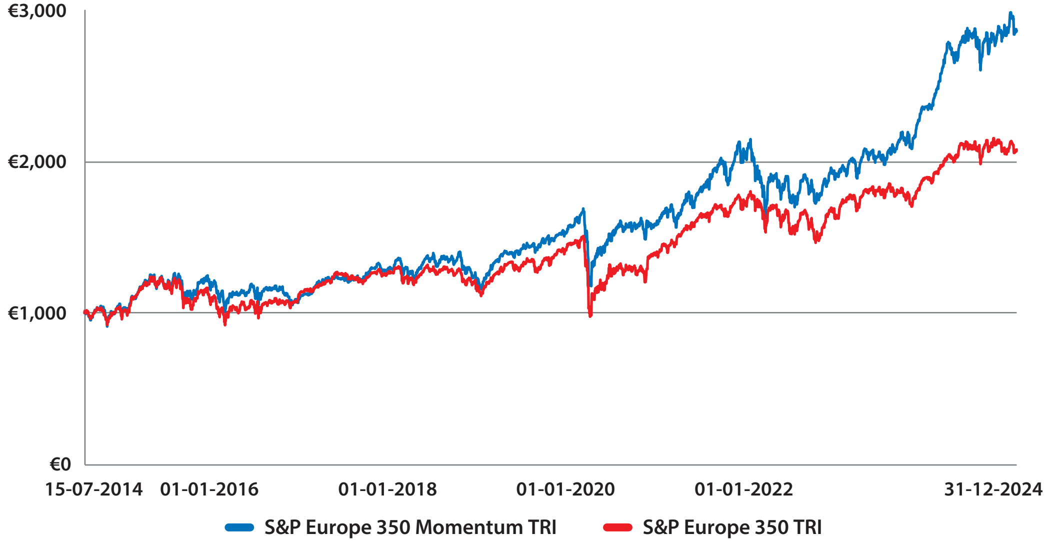


Momentum Vs Market: Value of $1000 Invested



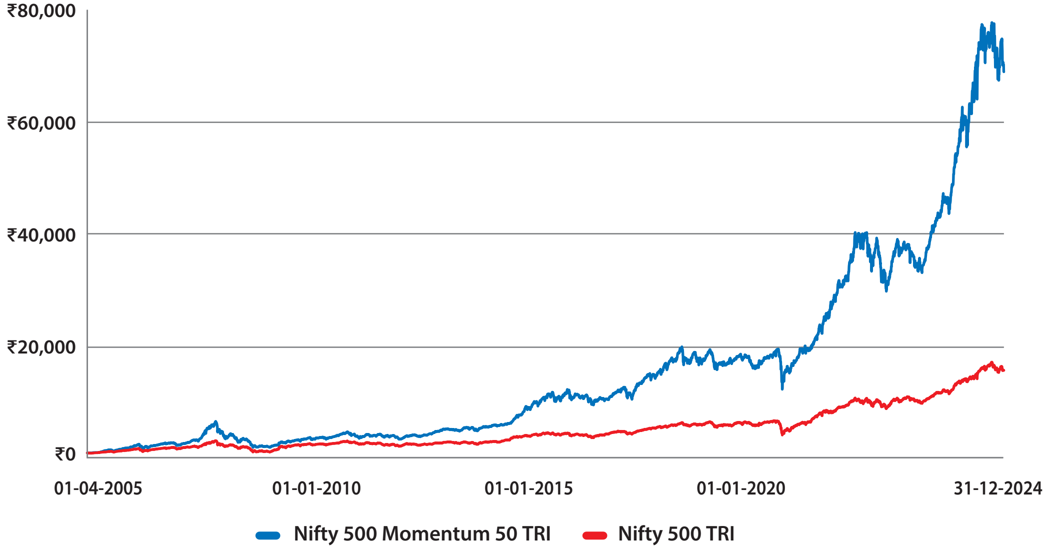
Source : Bloomberg. This chart depicts the growth in the NAV of S&P 500 Momentum TRI vis-a-vis that of the S&P 500 TRI over the period 5th July 1995 to 31st December 2024. All the NAVs are in USD and have not been converted to INR. All the indices have been scaled to $1,000 as of 5th July 1995. Past performance may or may not be sustained in future and is not an indication of future return.

Momentum Vs Market: Value of €1000 Invested

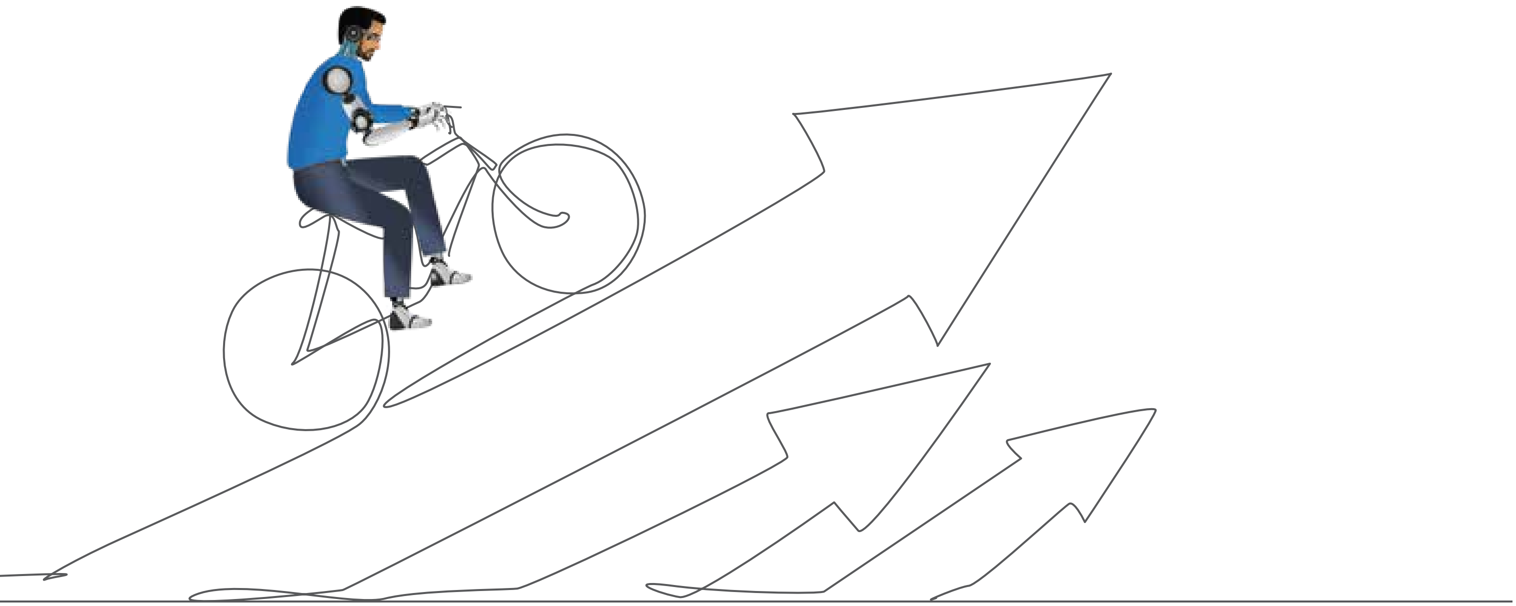


Source : Bloomberg. This chart depicts the growth in the NAV of S&P Europe 350 Momentum TRI vis-a-vis that of the S&P Europe 350 TRI over the period 15th July 2014 to 31st December 2024. All the NAVs are in EUR and have not been converted to INR. All the indices have been scaled to €1,000 as of 15th July 2014. Past performance may or may not be sustained in future and is not an indication of future return.

Momentum Vs Market: Value of ₹1000 Invested



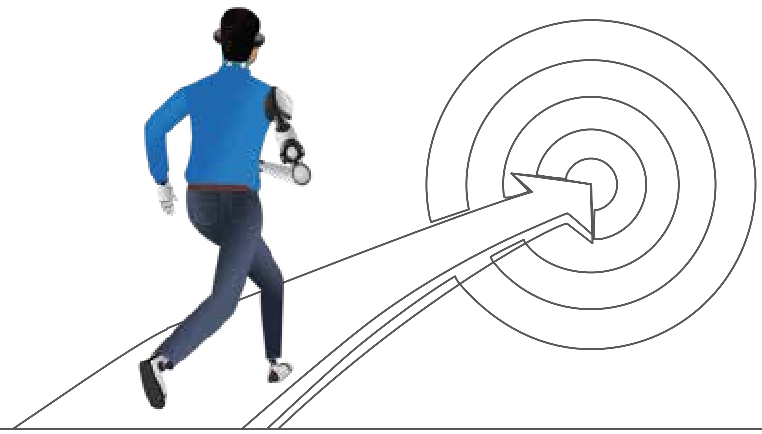
Source : NSE. This chart depicts the growth in the NAVs of Nifty 500 Momentum 50 TRI vis-a-vis that of the Nifty 500 TRI over the period 1st April 2005 to 31st December 2024. All the indices have been scaled to ₹1,000 as of 1st April 2005. Past performance may or may not be sustained in future and is not an indication of future return.



Period-wise Summary of Factor Performance: Momentum Vs Market

Region	Period	Annualised Return (%)		3-Year Median Rolling Return (%)		10-Year Median Rolling Return (%)	
		Momentum	Market	Momentum	Market	Momentum	Market
USA	Jul 5, 1995 - Dec 31, 2000	26.42	19.32	27.24	25.80	-	-
	Jan 1, 2001 - Dec 31, 2006	6.49	2.94	10.40	8.98	-	-
	Jan 1, 2007 - Dec 31, 2012	6.42	2.29	4.56	1.58	-	-
	Jan 1, 2013 - Dec 31, 2018	11.20	12.15	9.86	10.90	-	-
	Jan 1, 2019 - Dec 31, 2024	17.81	16.95	11.64	10.35	-	-
	Entire Period	13.21	10.36	11.81	11.20	11.00	7.98
Europe	Jul 15, 2014 - Dec 31, 2018	3.94	2.97	4.99	3.61	-	-
	Jan 1, 2019 - Dec 31, 2024	15.82	10.55	11.16	8.99	-	-
	Entire Period	10.59	7.25	8.90	7.60	10.84	7.60
India	Apr 1, 2005 - Dec 31, 2012	23.87	14.79	10.69	8.58	-	-
	Jan 1, 2013 - Dec 31, 2018	21.33	12.75	24.36	13.11	-	-
	Jan 1, 2019 - Dec 31, 2024	26.41	17.20	30.88	19.28	-	-
	Entire Period	23.89	14.96	19.77	13.11	20.98	12.75

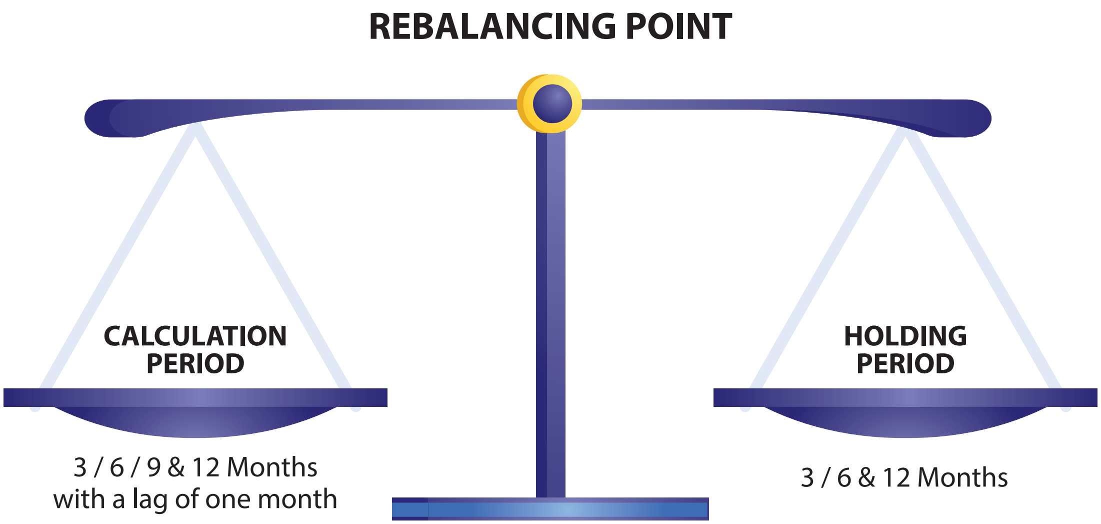
Source : Bloomberg, NSE. Past performance may or may not be sustained in future and is not an indication of future return. The S&P 500 Momentum TRI, S&P Europe 350 Momentum TRI, & Nifty 500 Momentum 50 TRI are used to represent the momentum index for the USA, Europe and India regions respectively. The S&P 500 TRI, S&P Europe 350 TRI, & Nifty 500 TRI are used to represent the market index for the USA, Europe and India regions respectively.



4.5 NJ's Momentum Factor - NJ Momentum+ Model

One of the concerns when using momentum is the propensity of a moving stock to "recoil" sharply when it reaches a turning point. The most popular way of overcoming this is to use a lag between the time when momentum is studied and when it is acted upon. This allows the "recoil", if it happens, to manifest and lower the acquisition cost of the stock.

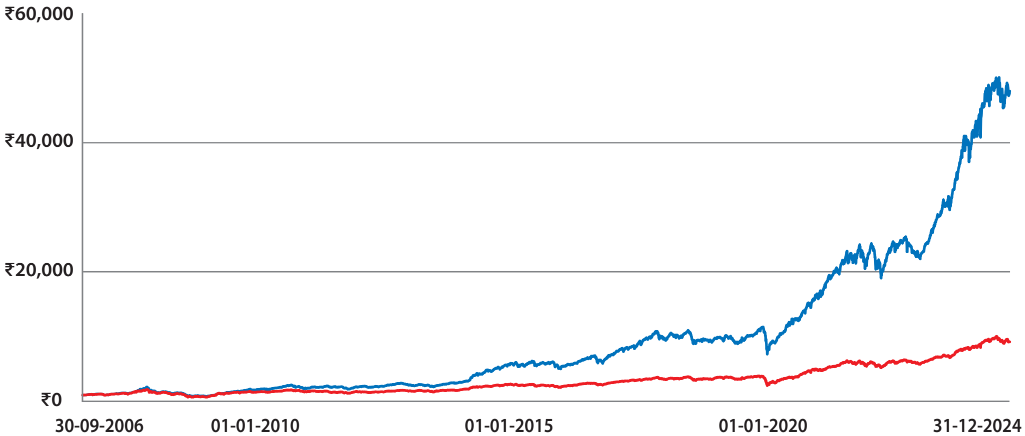
In developing our Momentum indicator, we studied various time periods between 1 and 12 months of standalone and comparative momentum. We studied these both with and without different lag periods from 5 days to 1 month. We also studied various holding periods for our resultant portfolio ranging from 3 to 12 months. In studying these, transaction costs were incorporated into the process to allow for a robust comparison of the outcomes achieved.



Our current methodology provides a balance between managing portfolio churn, factor decay, and scalability.

The NJ Momentum+ model combines the short term and long term momentum of a stock to rank it based on the combined score. It uses the past 3 months return to calculate the short term and the past 9 months returns to calculate the long term momentum. The NJ Momentum+ model chooses the Top 100 stocks with the highest momentum from the Nifty 500 index and constructs an equal weighting model.

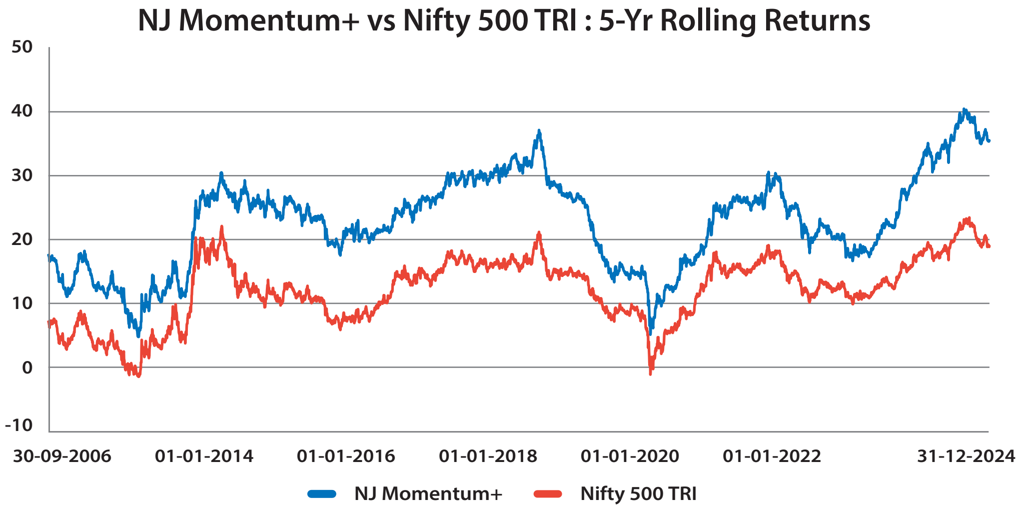
Value of ₹1000 Invested



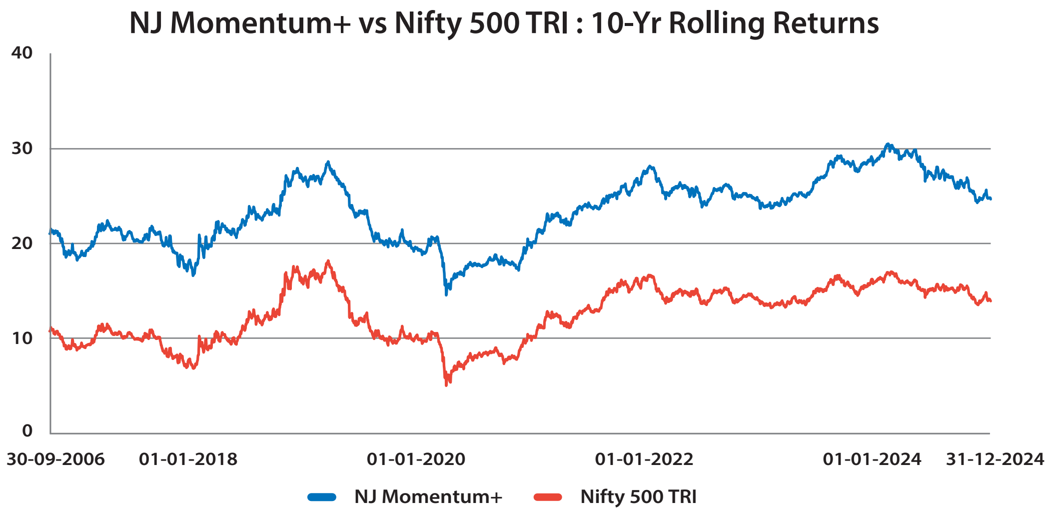
Source: Internal research, Bloomberg, CMIE, National Stock Exchange, NJ's Smart Beta Platform (in-house proprietary model of NJAMC). Calculations are for the period 30th September 2006 to 31st December 2024. NJ Momentum+ Model is an in-house proprietary methodology developed by NJ Asset Management Private Limited. The methodology will keep evolving with new insight based on the ongoing research and will be updated accordingly from time to time. Past performance may or may not be sustained in future and is not an indication of future return. The above is only for illustration purposes and should not be construed as indicative return of offering of NJ Asset Management Private Limited.

Parameter	1-Year Return	3-Year CAGR	5-Year CAGR	10-Year CAGR	Since Inception CAGR
NJ Momentum+	32.81%	27.96%	35.36%	24.63%	23.59%
Nifty 500 TRI	16.24%	15.43%	18.95%	13.93%	12.92%

Source : Internal research, Bloomberg, CMIE, National Stock Exchange. Data is as on 31st December 2024. Past performance may or may not be sustained in future and is not an indication of future return. NJ Momentum+ Model is a proprietary methodology developed by NJ Asset Management Private Limited. The methodology will keep evolving with new insight based on the ongoing research and will be updated accordingly from time to time.



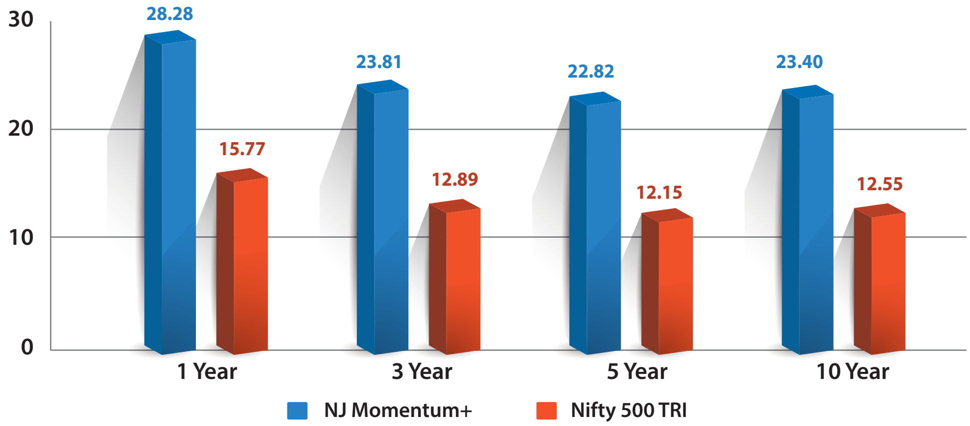
Source : Internal research, Bloomberg, CMIE, National Stock Exchange of India, NJ's Smart Beta Platform (in-house proprietary model of NJAMC). 5-Yr CAGRs are calculated for the period 30th September 2006 to 31st December 2024 and have been rolled on a daily basis. Past performance may or may not be sustained in future and is not indication of future return. NJ Momentum+ Model is a proprietary methodology developed by NJ Asset Management Private Limited. The methodology will keep evolving with new insight based on the ongoing research and will be updated accordingly from time to time.



Source : Internal research, Bloomberg, CMIE, National Stock Exchange of India, NJ's Smart Beta Platform (in-house proprietary model of NJAMC). 10-Yr CAGRs are calculated for the period 30th September 2006 to 31st December 2024 and have been rolled on a daily basis. Past performance may or may not be sustained in future and is not indication of future return. NJ Momentum+ Model is a proprietary methodology developed by NJ Asset Management Private Limited. The methodology will keep evolving with new insight based on the ongoing research and will be updated accordingly from time to time.

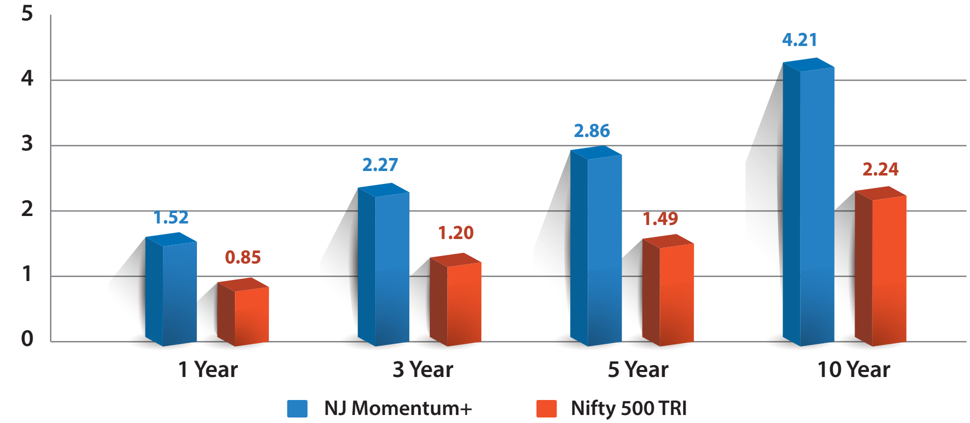
As the charts indicate, momentum has been a consistent outperformer across various time periods which makes it one of the most important factors in India. Since it offers the widest range of options to calculate and determine its presence, implementations of momentum differ very widely across the world and even within India. Combined with its fickle nature, the search for the most efficient and consistent way to measure momentum promises to be a long one.

NJ Momentum+ and Nifty 500 TRI: Average Rolling CAGR



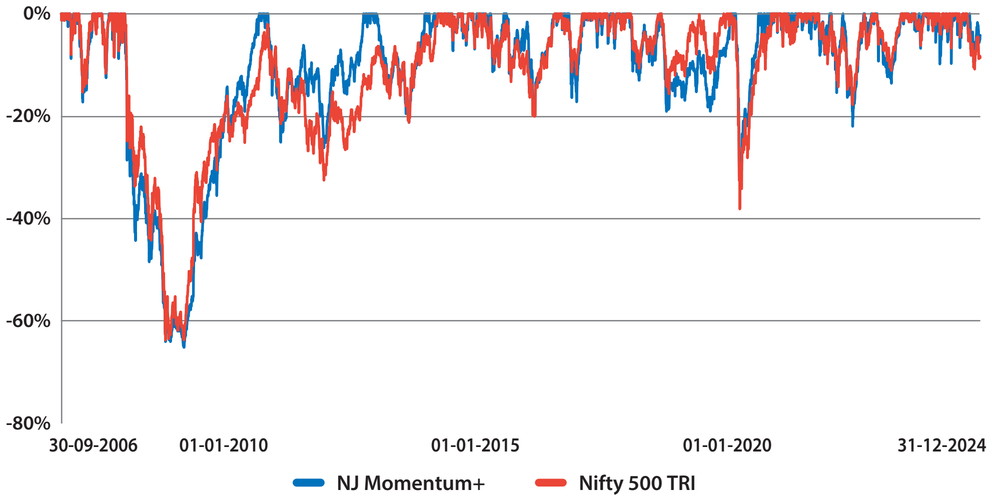
Source: Internal research, Bloomberg, CMIE, National Stock Exchange of India, NJ's Smart Beta Platform (in-house proprietary model of NJAMC). CAGRs are calculated as the average CAGR based on the rolling CAGRs (rolled daily) calculated for the respective holding periods i.e. 1, 3, 5, and 10-Yr rolling CAGRs. The period for calculation is 30th September 2006 to 31st December 2024. Past performance may or may not be sustained in future and is not an indication of future return. NJ Momentum+ Model is a proprietary methodology developed by NJ Asset Management Private Limited. The methodology will keep evolving with new insight based on the ongoing research and will be updated accordingly from time to time.

NJ Momentum+ and Nifty 500 TRI: Return/Standard Deviation



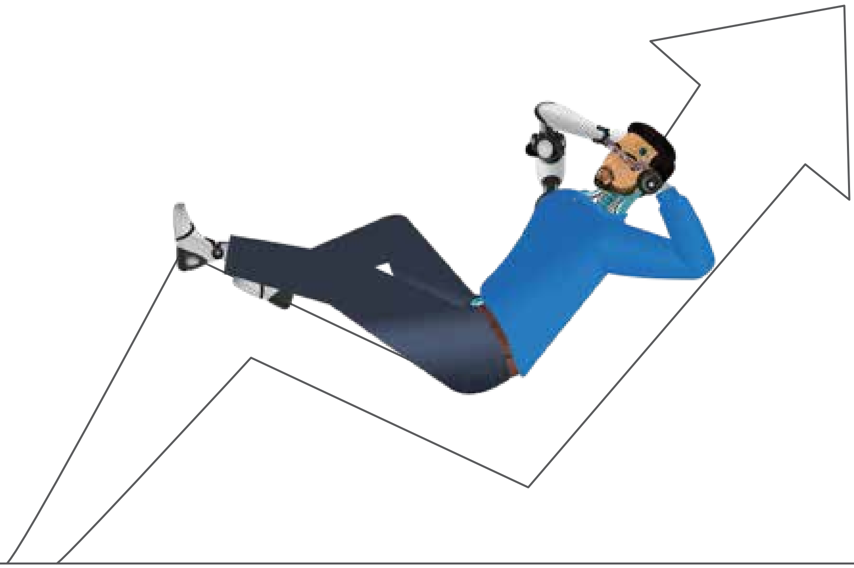
Source: Internal research, Bloomberg, CMIE, National Stock Exchange of India, NJ's Smart Beta Platform (in-house proprietary model of NJAMC). The Return/Standard Deviation ratios have been calculated by dividing the respective rolling returns (rolled daily) by the standard deviation of the corresponding rolling returns, The period for calculation is 30th September 2006 to 31st December 2024. Past performance may or may not be sustained in future and is not an indication of future return. NJ Momentum+ Model is a proprietary methodology developed by NJ Asset Management Private Limited. The methodology will keep evolving with new insight based on the ongoing research and will be updated accordingly from time to time.

NJ Momentum+ vs Nifty 500: Maximum Drawdown



	NJ Momentum+	Nifty 500 TRI
Maximum Drawdown	-65.11%	-63.71%

Source: Internal research, Bloomberg, CMIE, National Stock Exchange of India, NJ's Smart Beta Platform (in-house proprietary model of NJAMC). Calculations are for the period 30th September 2006 to 31st December 2024. The Drawdown for a specific date has been calculated by dividing that day's NAV of NJ Momentum+ Model and Nifty 500 TRI by their peak NAVs up to that date, respectively. Past performance may or may not be sustained in future and is not an indication of future return. NJ Momentum+ Model is a proprietary methodology developed by NJ Asset Management Private Limited. The methodology will keep evolving with new insight based on the ongoing research and will be updated accordingly from time to time.



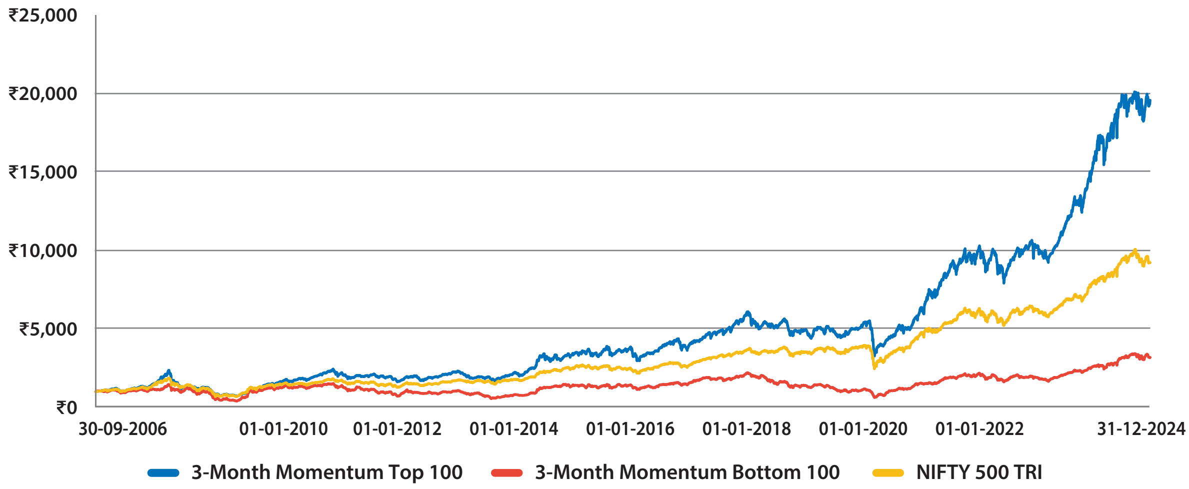
4.6 Performance of Select Momentum Parameters

A. Momentum

- Momentum refers to the absolute price movement of an asset over a specific time period. It is typically measured as the difference or percentage change between the asset's price at the end of the period and its price at the beginning of the period.
- Example:
  Calculating 9-Month momentum
- Start date: 31-03-2023
  Price at start date: ₹1,023.14
  End date: 31-12-2023
  Price at end date: ₹1,546.29

Absolute return/momentum: ((Price at end date - price at start date) / price at start date) * 100
((1546.29-1023.14)/1023.14) * 100 = 51.13%

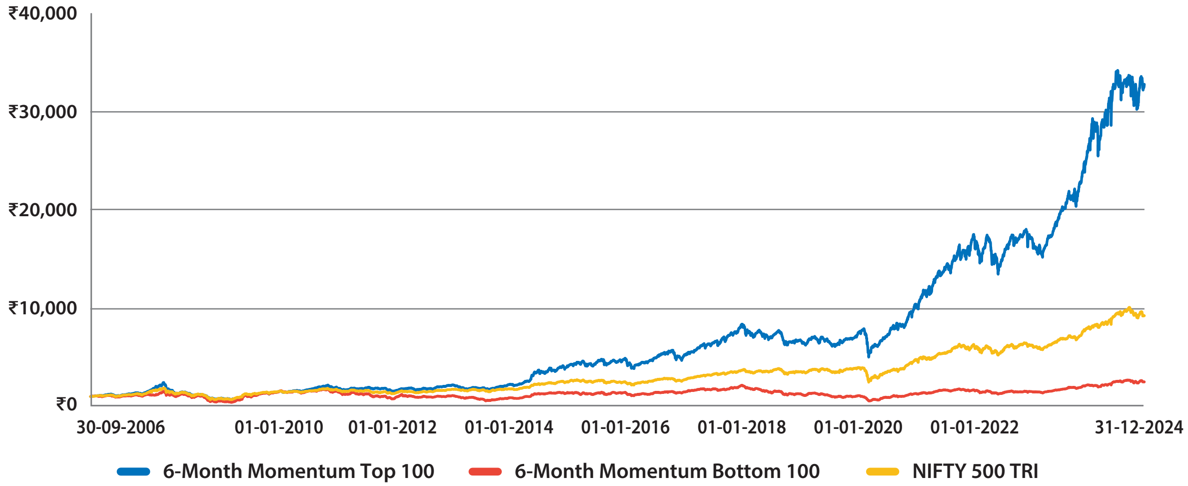
High Vs Low 3-Month Momentum



From Sep 2006 to Dec 2024	CAGR (%)	10 Year Median Rolling Returns (%)	Annualised Volatility (%)	Maximum Drawdown (%)	Cumulative Growth of 1000
3-Month Momentum Top 100	17.68	16.02	21.59	-70.17	₹19,567
3-Month Momentum Bottom 100	6.55	6.25	23.81	-72.87	₹3,185
Nifty 500 TRI	12.92	13.03	20.18	-63.71	₹9,214

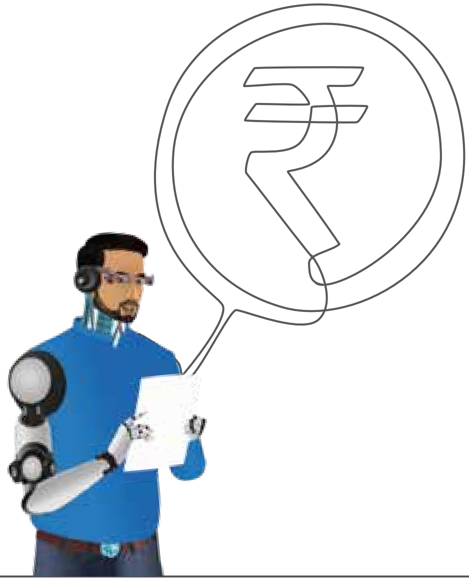
Source: CMIE, NJ's Smart Beta Platform. Data for the period 30th September 2006 to 31st December 2024. Past performance may or may not be sustained in future and is not indication of future return.

High Vs Low 6-Month Momentum

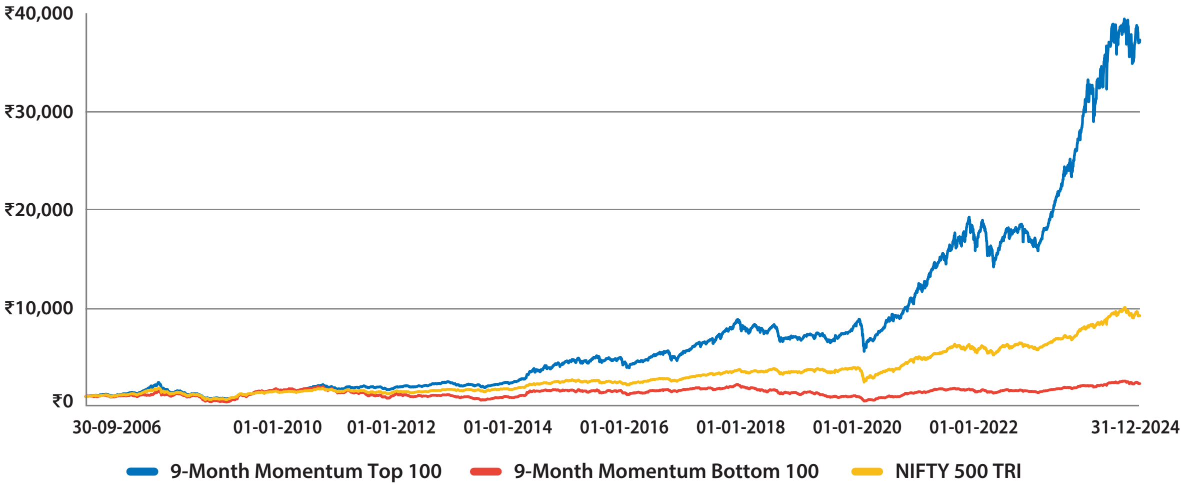


From Sep 2006 to Dec 2024	CAGR (%)	10 Year Median Rolling Returns (%)	Annualised Volatility (%)	Maximum Drawdown (%)	Cumulative Growth of 1000
6-Month Momentum Top 100	21.04	22.07	21.35	-70.75	₹32,766
6-Month Momentum Bottom 100	5.12	4.21	24.25	-74.83	₹2,490
Nifty 500 TRI	12.92	13.03	20.18	-63.71	₹9,214

Source: CMIE, NJ's Smart Beta Platform. Data for the period 30th September 2006 to 31st December 2024. Past performance may or may not be sustained in future and is not indication of future return.

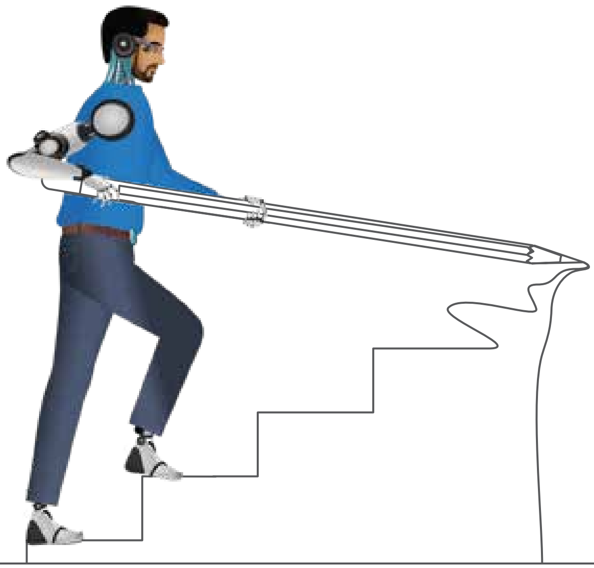


High Vs Low 9-Month Momentum

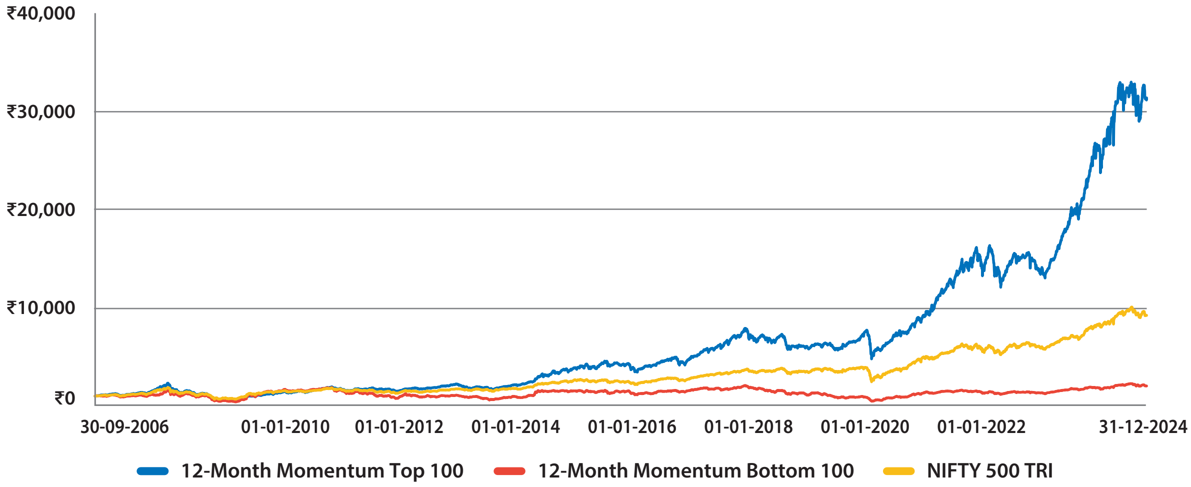


From Sep 2006 to Dec 2024	CAGR (%)	10 Year Median Rolling Returns (%)	Annualised Volatility (%)	Maximum Drawdown (%)	Cumulative Growth of 1000
9-Month Momentum Top 100	21.90	21.79	21.10	-68.70	₹37,279
9-Month Momentum Bottom 100	4.71	4.30	24.66	-76.58	₹2,318
Nifty 500 TRI	12.92	13.03	20.18	-63.71	₹9,214

Source: CMIE, NJ's Smart Beta Platform. Data for the period 30th September 2006 to 31st December 2024. Past performance may or may not be sustained in future and is not indication of future return.



High Vs Low 12-Month Momentum



From Sep 2006 to Dec 2024	CAGR (%)	10 Year Median Rolling Returns (%)	Annualised Volatility (%)	Maximum Drawdown (%)	Cumulative Growth of 1000
12-Month Momentum Top 100	20.76	20.99	21.10	-71.72	₹31,378
12-Month Momentum Bottom 100	3.95	3.67	24.97	-77.45	₹2,030
Nifty 500 TRI	12.92	13.03	20.18	-63.71	₹9,214

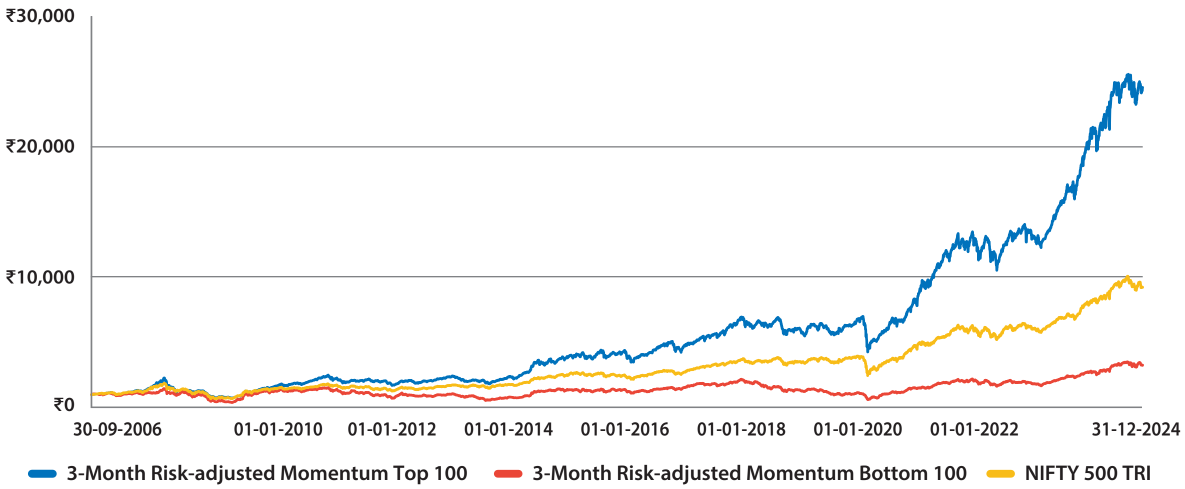
Source: CMIE, NJ's Smart Beta Platform. Data for the period 30th September 2006 to 31st December 2024. Past performance may or may not be sustained in future and is not indication of future return.

B. Risk-adjusted Momentum

- Risk-adjusted Momentum adjusts the raw momentum by incorporating the volatility of the asset's returns during the same period. It measures the momentum in a way that accounts for risk, making it more comparable across different assets or markets with varying risk profiles.
- Risk-adjusted Momentum = Momentum / Volatility
- Example:
  Continuing the previous example, if we decide to scale the momentum by 12-month Daily volatility (Standard Deviation) for Stock A, that comes out to be 21.68%

Risk-adjusted Momentum = 51.13 / 21.68 = 2.35

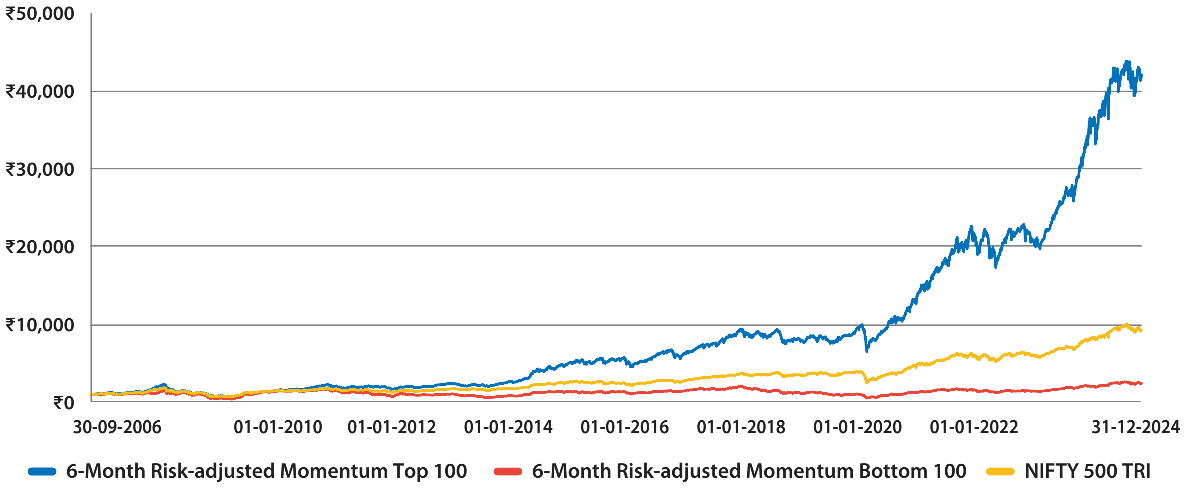
High Vs Low 3-Month Risk-adjusted Momentum



From Sep 2006 to Dec 2024	CAGR (%)	10 Year Median Rolling Returns (%)	Annualised Volatility (%)	Maximum Drawdown (%)	Cumulative Growth of 1000
3-Month Risk-adjusted Momentum Top 100	19.14	18.40	20.05	-68.20	₹24,532
3-Month Risk-adjusted Momentum Bottom 100	6.68	6.22	23.96	-73.17	₹3,261
Nifty 500 TRI	12.92	13.03	20.18	-63.71	₹9,214

Source: CMIE, NJ's Smart Beta Platform. Data for the period 30th September 2006 to 31st December 2024. Past performance may or may not be sustained in future and is not indication of future return.

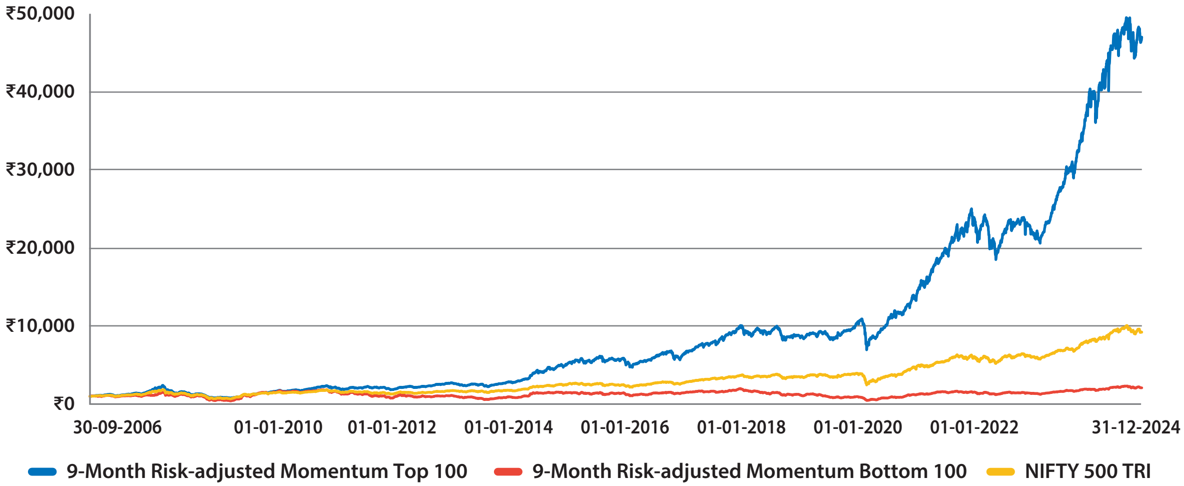
High Vs Low 6-Month Risk-adjusted Momentum



From Sep 2006 to Dec 2024	CAGR (%)	10 Year Median Rolling Returns (%)	Annualised Volatility (%)	Maximum Drawdown (%)	Cumulative Growth of 1000
6-Month Risk-adjusted Momentum Top 100	22.71	23.91	20.01	-69.34	₹42,068
6-Month Risk-adjusted Momentum Bottom 100	4.97	4.05	24.44	-74.83	₹2,426
Nifty 500 TRI	12.92	13.03	20.18	-63.71	₹9,214

Source: CMIE, NJ's Smart Beta Platform. Data for the period 30th September 2006 to 31st December 2024. Past performance may or may not be sustained in future and is not indication of future return.

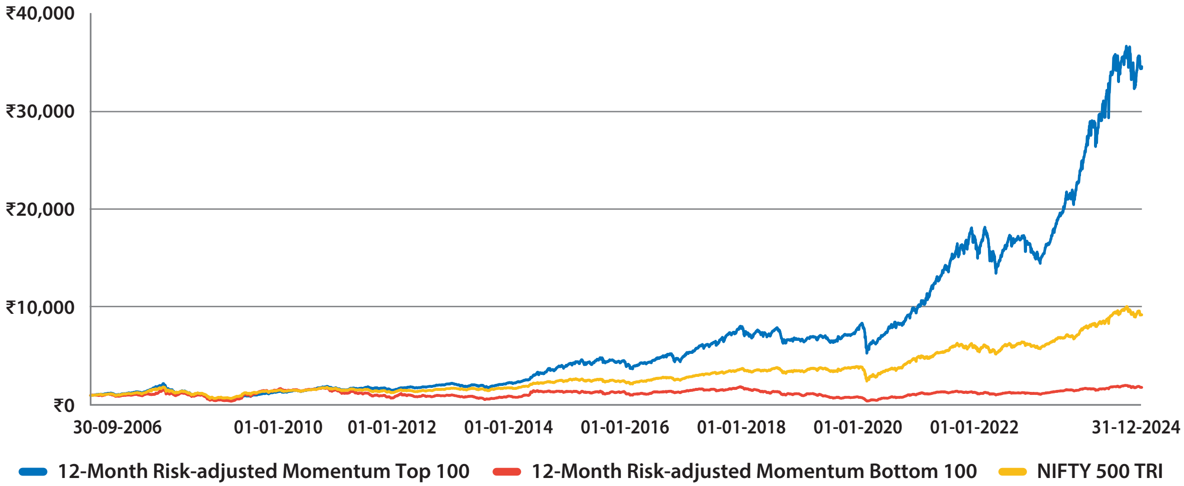
High Vs Low 9-Month Risk-adjusted Momentum



From Sep 2006 to Dec 2024	CAGR (%)	10 Year Median Rolling Returns (%)	Annualised Volatility (%)	Maximum Drawdown (%)	Cumulative Growth of 1000
9-Month Risk-adjusted Momentum Top 100	21.90	23.81	21.10	-70.75	₹32,766
9-Month Risk-adjusted Momentum Bottom 100	4.71	3.62	24.66	-74.83	₹2,490
Nifty 500 TRI	12.92	13.03	20.18	-63.71	₹9,214

Source: CMIE, NJ's Smart Beta Platform. Data for the period 30th September 2006 to 31st December 2024. Past performance may or may not be sustained in future and is not indication of future return.

High Vs Low 12-Month Risk-adjusted Momentum



From Sep 2006 to Dec 2024	CAGR (%)	10 Year Median Rolling Returns (%)	Annualised Volatility (%)	Maximum Drawdown (%)	Cumulative Growth of 1000
12-Month Risk-adjusted Momentum Top 100	21.40	22.15	19.91	-71.75	₹34,543
12-Month Risk-adjusted Momentum Bottom 100	3.33	2.90	25.13	-77.85	₹1,818
Nifty 500 TRI	12.92	13.03	20.18	-63.71	₹9,214

Source: CMIE, NJ's Smart Beta Platform. Data for the period 30th September 2006 to 31st December 2024. Past performance may or may not be sustained in future and is not indication of future return.

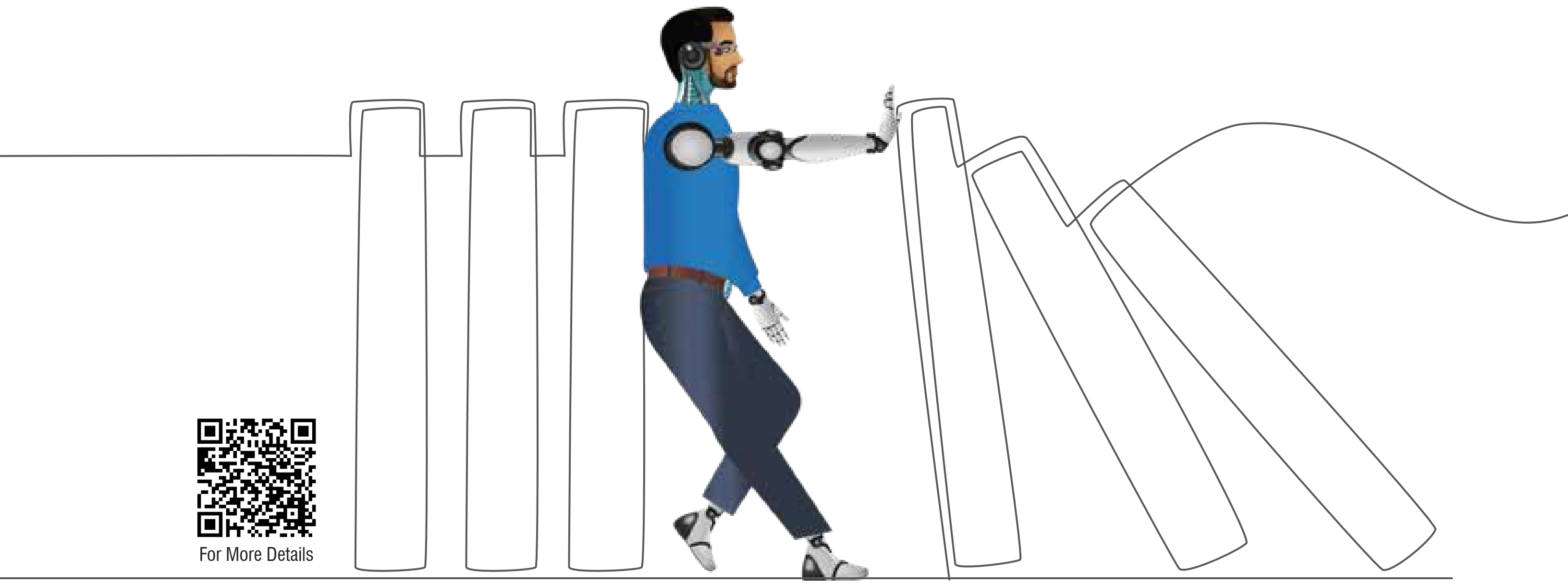
5. Low Volatility **Factor**

Superior investors make more money in good times than they give back in bad times.

-Howard Marks

It's not whether you're right or wrong that's important, but how much money you make when you're right and how much you lose when you're wrong.

-George Soros



For More Details

5. Low Volatility **Factor**

5.1 What is 'Low Volatility' Investing?

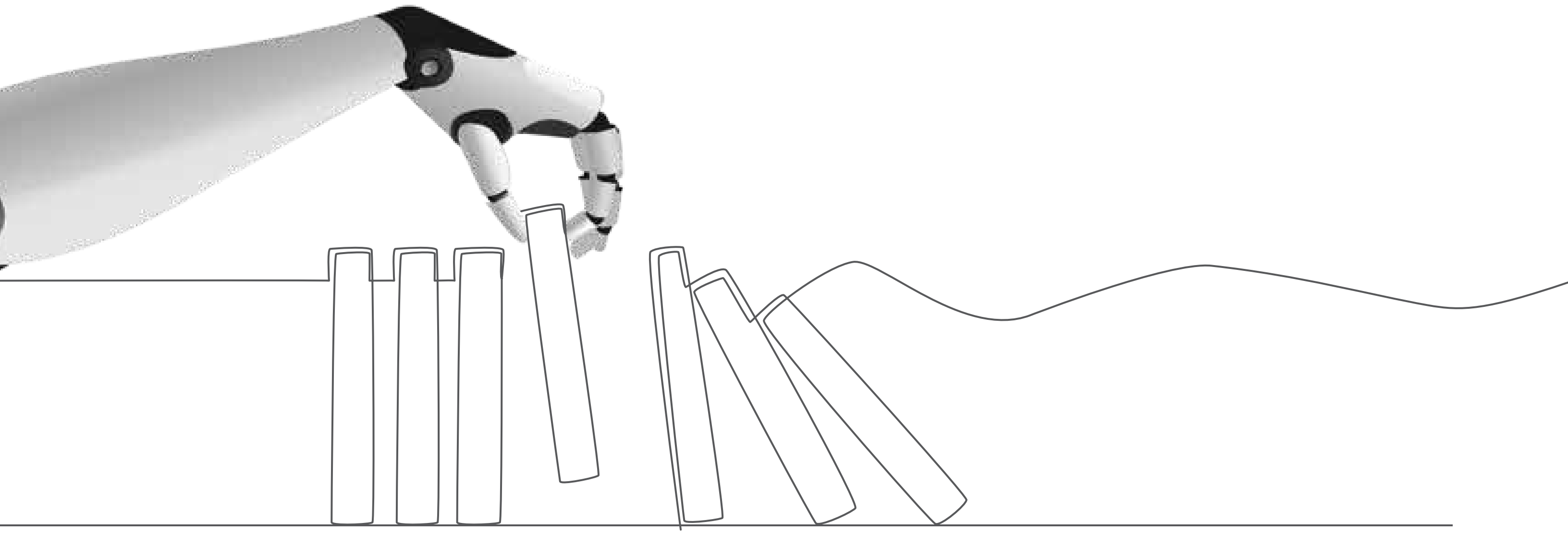
As on February 20, 2022 the batsman with the best strike rate in men's one day internationals is Andre Russell of the West Indies scoring 130.22 runs for every 100 balls faced. He is followed by Glen Maxwell of Australia (125.43) and Jos Buttler of England (118.66) (ESPN Sports Media, 2022a).

Fast scoring and exciting as they most certainly are, these same players are nowhere close to the top ranked when it comes to consistency, which is signified by career batting averages. Russell and Maxwell don't even make it to the top 100 with Buttler sneaking in at 95th rank with career batting averages of 27, 34 and 39 respectively (ESPN Sports Media, 2022b).

While every team needs fast scorers, the foundation for its performance is often provided by those who provide the highest consistency; the kind provided by a Virat Kohli and Michael Bevan with career averages of 58 and 53 (ESPN Sports Media, 2019), respectively (ESPN Sports Media, 2022b).

How does this kind of consistency relate to the world of investing? In investing, avoiding large losses can be far more important than making big profits. Investment success can be achieved by being consistently right even if it means that the gains from each investment are not the highest. Low volatility stocks offer this consistency to a portfolio.

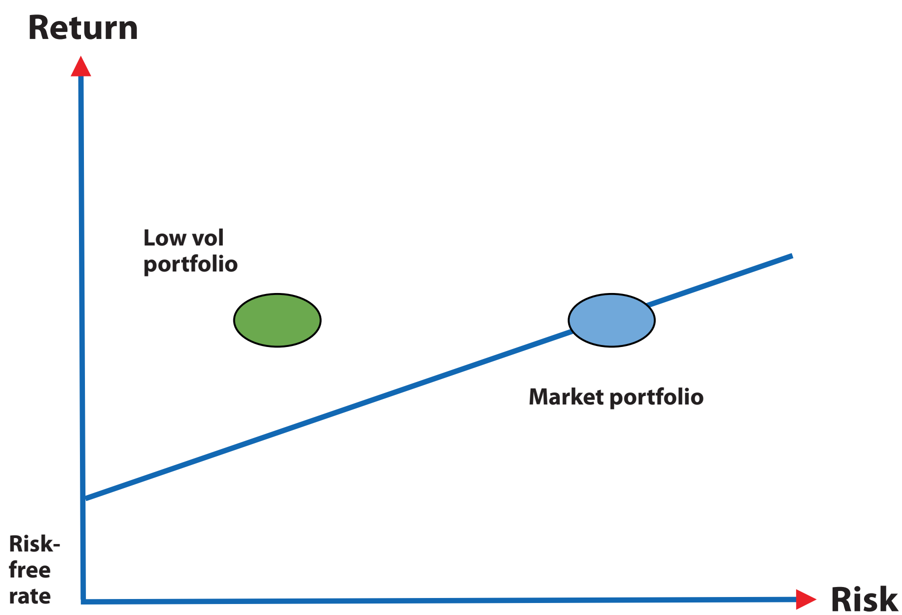
The low volatility factor targets securities with lower volatility characteristics. This typically translates into generally more consistent returns with lower deviations from long term means.



Several studies, including those conducted by Haugen and Heins (Haugen & Heins, 1972) as well as Frazzini (Frazzini & Pedersen, 2014), have demonstrated the existence of the Low Volatility Effect with empirical evidence of the ability of low volatility stocks to generate better risk-adjusted returns versus high volatility stocks on average, in US, European as well as emerging markets.

Also, many institutional and some retail investors deploy low volatility strategies to lower portfolio risk. The diagram below depicts how low volatility stocks can move the risk-return positioning of a portfolio to a superior position.

Volatility is usually measured using common statistical tools like standard deviation and semivariance. Like momentum, it offers vast choices in the period for which and over which it is computed, the holding period and whether one uses a single period of analysis or multiple ones.



Source : Illustration purpose only

5.2 How is 'Low Volatility' measured?

With a wide array of options there is no standard approach that has emerged as a dominant one among investment managers and index providers. And while standard deviation or related measures are quite popular, the periods of computation differ significantly. The table below describes the different types of low volatility factor indices across the world and the parameters used in their construction.

Index Details	Factor Characteristics	Methodology
Index Name: S&P 500 Low Volatility Index (US) Index Provider: S&P Dow Jones Indices LLC	Standard Deviation of Daily Price Returns (Last 1 Yr / approx 252 trading days)	Tilt the S&P 500 Index (capitalisation-weighted) towards 100 constituents with lowest volatilities, ranked inversely in terms of their realised volatilities.
Index Name: MSCI USA Minimum Volatility Index (USD) Index Provider: MSCI Inc.	Overall portfolio variance using individual variances and covariances between returns of constituents in the Parent Index	Tilt MSCI USA Index (capitalisation-weighted) towards an optimised portfolio which reduces the portfolio's overall volatility
Index Name: Nasdaq Factor Family US Low Volatility Index Index Provider: Nasdaq, Inc	Volatility Change Score and Volatility Strength Score based on realised standard deviation	Tilt Nasdaq US 500 Large Cap Index (capitalisation-weighted) towards 50 constituents having the lowest Volatility Strength Scores, with their weights being inversely proportional to the realised volatilities
Index Name: Nifty 100 Low Volatility 30 Index Index Provider: NSE Indices Ltd	Standard deviation of daily price returns (log-normal) over last 1-Yr period	Tilting Nifty 100 Index (capitalisation-weighted) towards 30 constituents with lowest volatility scores, with their weights being inversely proportional to the realised volatilities

Source: FTSE Russell, Research Affiliates, LLC, MSCI Inc, S&P Dow Jones Indices LLC, Nasdaq, Inc & NSE Indices Ltd

5.3 Does the Low Volatility Factor work?

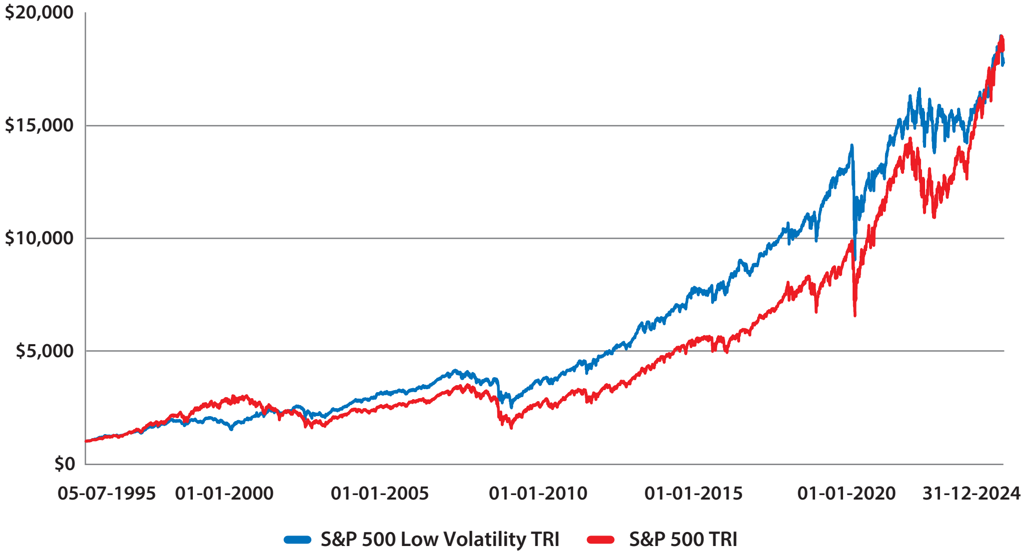
Typically, stocks with low volatility characteristics reward investors with higher risk-adjusted returns compared to a broad market capitalisation strategy over the long term. The benefit of using the low volatility factor became evident among institutional investors in the wake of the Global Financial Crisis (GFC) in 2008 and the Euro Debt Crisis.

In a study covering two decades and all stocks traded on the Bombay Stock Exchange, Agarwalla et al. find that lower volatility stocks can generate superior returns compared to high volatility stocks (Arunachalam et al., 2020,). The authors believe that the lack of access to leverage for stock market investments encourages investors to seek higher risk stocks in an effort to achieve the highest expected return.

5.4 Performance of Low Volatility Factor Across Markets: USA, Europe, and India

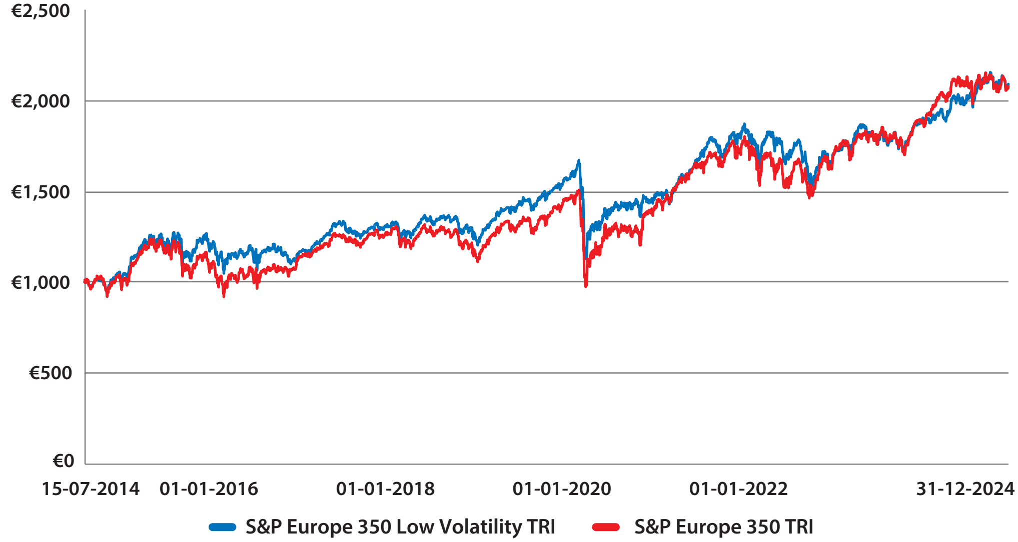
The performance of the low volatility factor across the USA, Europe, and India, as depicted in the graphs, highlights the growth of a $1000 (or local currency equivalent) investment in the respective low volatility index versus its broad market benchmark, demonstrating how this factor has historically performed.

Low Volatility Vs Market: Value of $1000 Invested



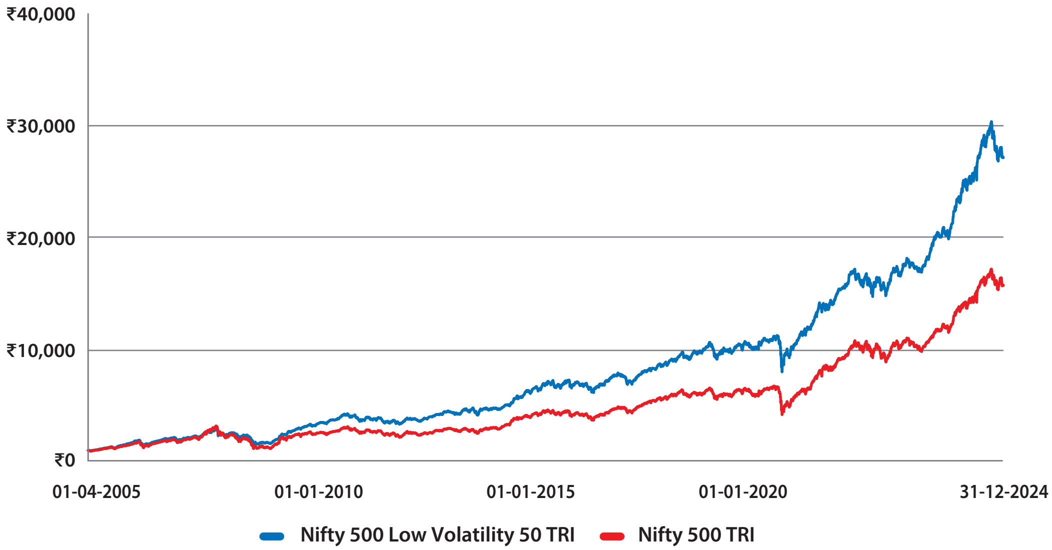
Source : Bloomberg. This chart depicts the growth in the NAV of S&P 500 Low Volatility TRI vis-a-vis that of the S&P 500 TRI over the period 5th July 1995 to 31st December 2024. All the NAVs are in USD and have not been converted to INR. All the indices have been scaled to $1,000 as of 5th July 1995. Past performance may or may not be sustained in future and is not an indication of future return.

Low Volatility Vs Market: Value of €1000 Invested

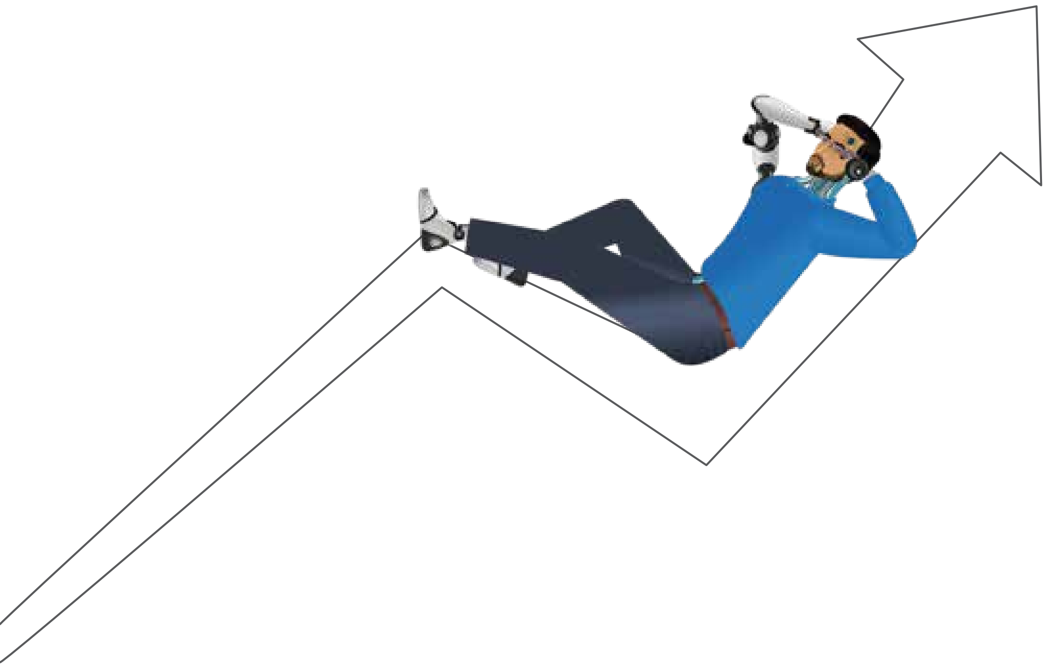


Source : Bloomberg. This chart depicts the growth in the NAV of S&P Europe 350 Low Volatility TRI vis-a-vis that of the S&P Europe 350 TRI over the period 15th July 2014 to 31st December 2024. All the NAVs are in EUR and have not been converted to INR. All the indices have been scaled to €1,000 as of 15th July 2014. Past performance may or may not be sustained in future and is not an indication of future return.

Low Volatility Vs Market: Value of ₹1000 Invested



Source : NSE. This chart depicts the growth in the NAVs of Nifty 500 Low Volatility 50 TRI vis-a-vis that of the Nifty 500 TRI over the period 1st April 2005 to 31st December 2024. All the indices have been scaled to ₹1,000 as of 1st April 2005. Past performance may or may not be sustained in future and is not an indication of future return.



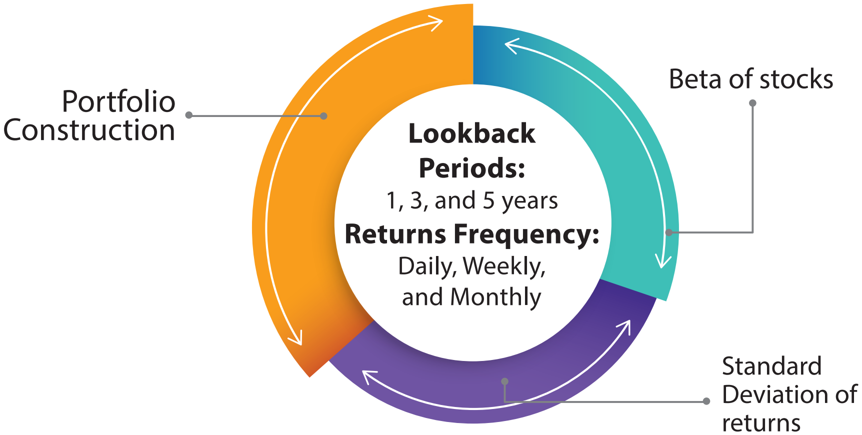
Period-wise Summary of Factor Performance: Low Volatility Vs Market

Region	Period	Annualised Return (%)		3-Year Median Rolling Return (%)		10-Year Median Rolling Return (%)	
		Low Vol.	Market	Low Vol.	Market	Low Vol.	Market
USA	Jul 5, 1995 - Dec 31, 2000	16.07	19.32	12.92	25.80	-	-
	Jan 1, 2001 - Dec 31, 2006	9.38	2.94	11.04	8.98	-	-
	Jan 1, 2007 - Dec 31, 2012	5.16	2.29	6.28	1.58	-	-
	Jan 1, 2013 - Dec 31, 2018	11.95	12.15	11.41	10.90	-	-
	Jan 1, 2019 - Dec 31, 2024	9.46	16.95	6.27	10.35	-	-
	Entire Period	10.25	10.36	10.18	11.20	9.46	7.98
Europe	Jul 15, 2014 - Dec 31, 2018	4.78	2.97	3.85	3.61	-	-
	Jan 1, 2019 - Dec 31, 2024	9.24	10.55	7.45	8.99	-	-
	Entire Period	7.31	7.25	6.63	7.60	7.50	7.60
India	Apr 1, 2005 - Dec 31, 2012	21.27	14.79	16.61	8.58	-	-
	Jan 1, 2013 - Dec 31, 2018	14.31	12.75	14.11	13.11	-	-
	Jan 1, 2019 - Dec 31, 2024	18.06	17.20	19.63	19.28	-	-
	Entire Period	18.17	14.96	15.69	13.11	15.29	12.75

Source : Bloomberg, NSE. Past performance may or may not be sustained in future and is not an indication of future return. The S&P 500 Low Volatility TRI, S&P Europe 350 Low Volatility TRI, & Nifty 500 Low Volatility 50 TRI are used to represent the low volatility index for the USA, Europe and India regions respectively. The S&P 500 TRI, S&P Europe 350 TRI, & Nifty 500 TRI are used to represent the market index for the USA, Europe and India regions respectively.

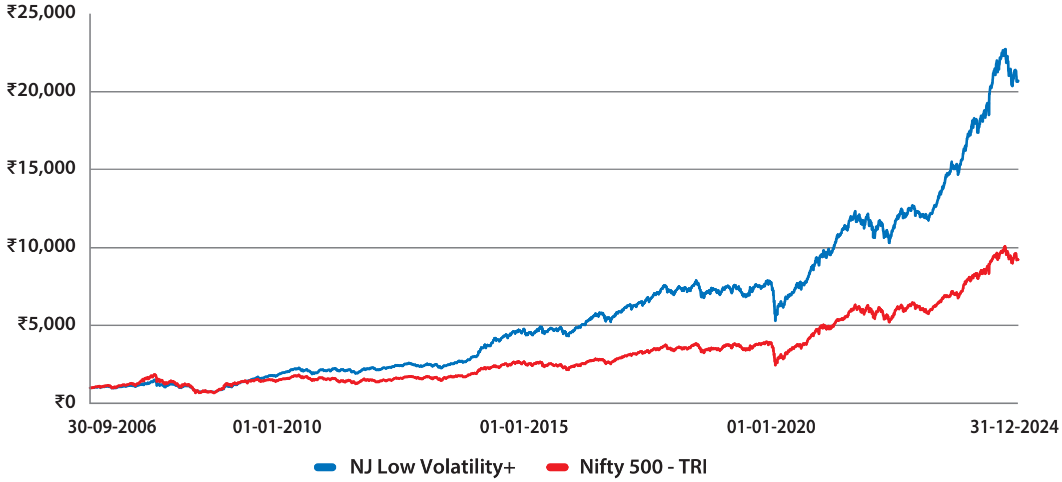
5.5 NJ's Low Volatility Factor - NJ Low Volatility+ Model

One of the main concerns of focusing on lower volatility stocks is that they can generate lower returns than the market. Due to its unique structural aspects, historical data has shown that this has not held true in the Indian context. After studying daily, weekly, and monthly volatility over various time periods and holding periods, we follow a measure that provides the optimal mix of consistency and churn.



The NJ Low Volatility+ model uses the past 36 months price history to calculate the volatility of a stock. The NJ Low Volatility+ model chooses the Top 100 stocks with the lowest volatility from the Nifty 500 universe and constructs an equal weighting model. The model displays the following characteristics vis-a-vis the benchmark Nifty 500 TRI.

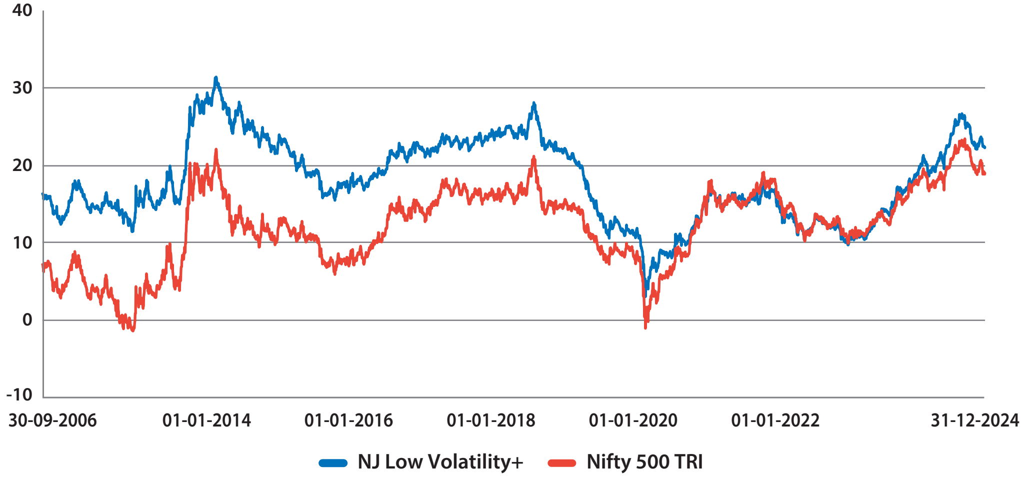
Value of ₹1000 Invested



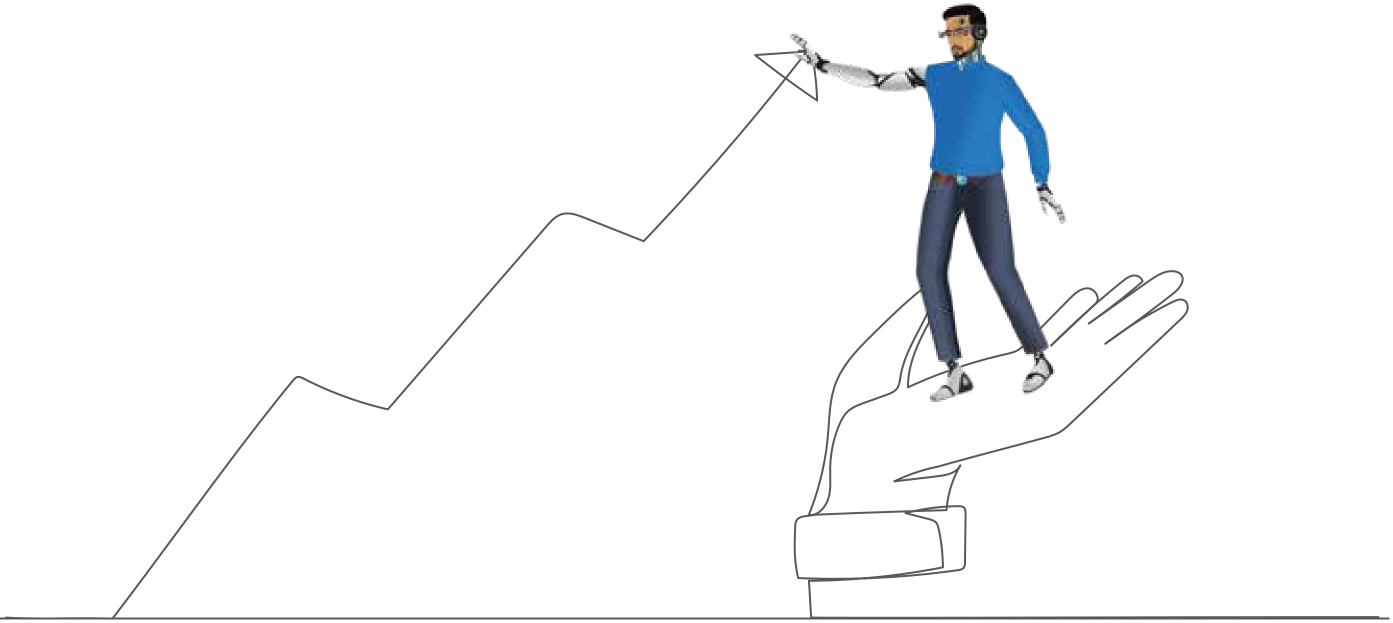
	36-Month Volatility (%)	36-Month Beta	36-Month Semi-Deviation (%)
NJ Low Volatility+	11.91	0.77	8.59
Nifty 500	14.26	1.00	10.46

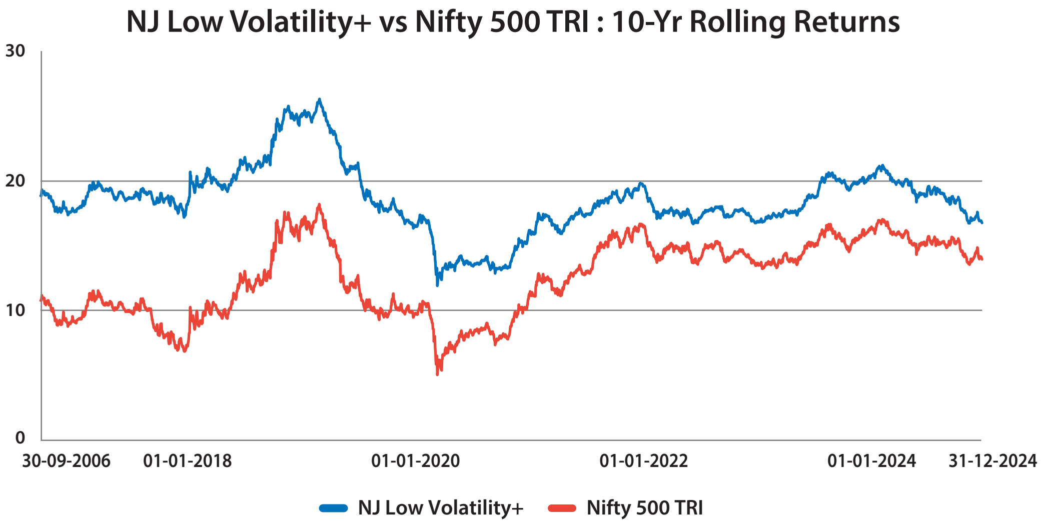
Source: Internal research, Bloomberg, CMIE, National Stock Exchange, NJ's Smart Beta Platform (in-house proprietary model of NJAMC). Factor parameters calculated as on 31st December 2024. For Nifty 500 TRI & NJ Low Volatility+ Model factor definitions are the average of its constituents. Volatility is calculated using daily returns annualised. Beta is calculated as the covariances of the security with the market divided by the variance of the market. Semi deviation is defined as downside standard deviation annualised. Past performance may or may not be sustained in future and is not an indication of future return. NJ Low Volatility+ Model is a proprietary methodology developed by NJ Asset Management Private Limited. The methodology will keep evolving with new insight based on the ongoing research and will be updated accordingly from time to time.

NJ Low Volatility+ vs Nifty 500 TRI : 5-Yr Rolling Returns



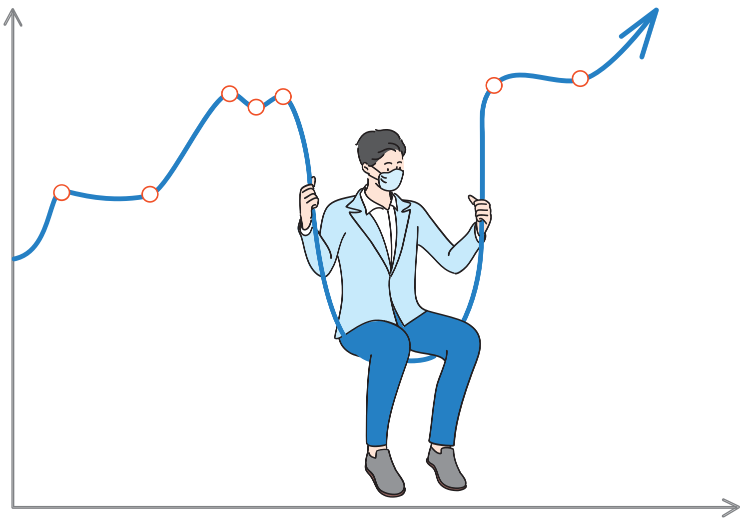
Source: Internal research, Bloomberg, CMIE, National Stock Exchange of India, NJ's Smart Beta Platform (in-house proprietary model of NJAMC). 5-Yr CAGRs are calculated for the period 30th September 2006 to 31st December 2024 and have been rolled on a daily basis. Past performance may or may not be sustained in future and is not indication of future return. NJ Low Volatility+ Model is a proprietary methodology developed by NJ Asset Management Private Limited. The methodology will keep evolving with new insight based on the ongoing research and will be updated accordingly from time to time.



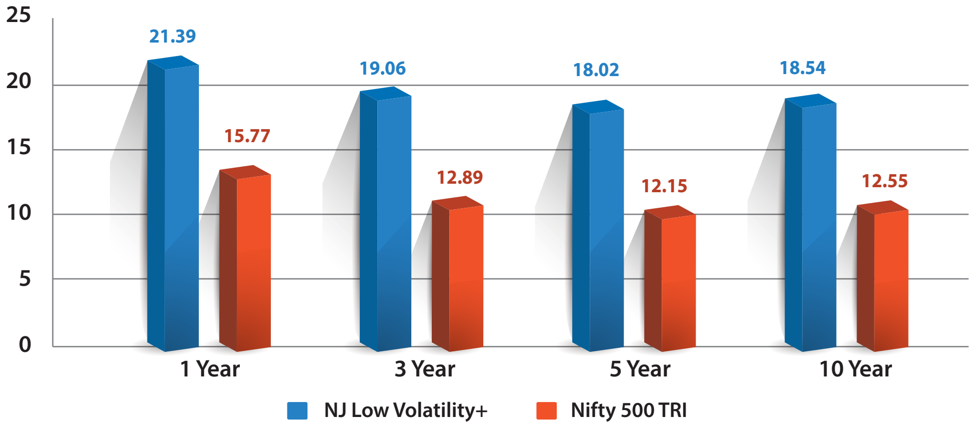


Source: Internal research, Bloomberg, CMIE, National Stock Exchange of India, NJ's Smart Beta Platform (in-house proprietary model of NJAMC). 10-Yr CAGRs are calculated for the period 30th September 2006 to 31st December 2024 and have been rolled on a daily basis. Past performance may or may not be sustained in future and is not indication of future return. NJ Low Volatility+ Model is a proprietary methodology developed by NJ Asset Management Private Limited. The methodology will keep evolving with new insight based on the ongoing research and will be updated accordingly from time to time.

The low volatility factor lives up to its promise of generating additional returns compared to the index with lower deviation and greater consistency.

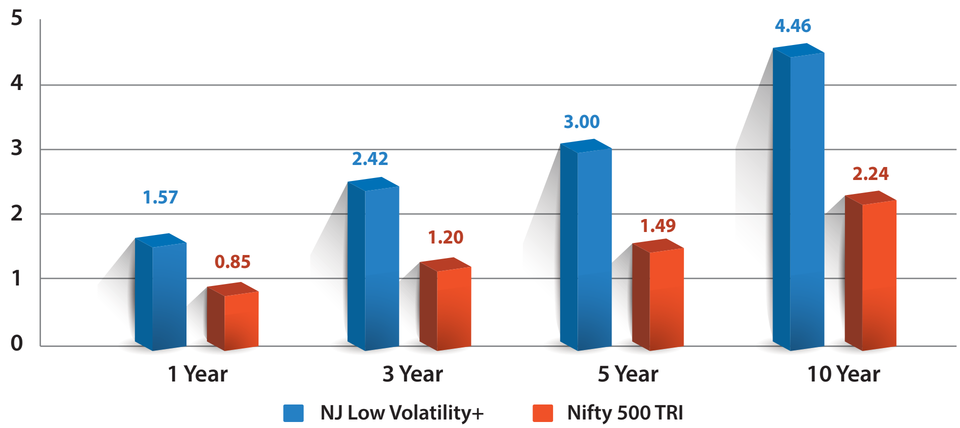


NJ Low Volatility+ vs Nifty 500 TRI : Average Rolling CAGR



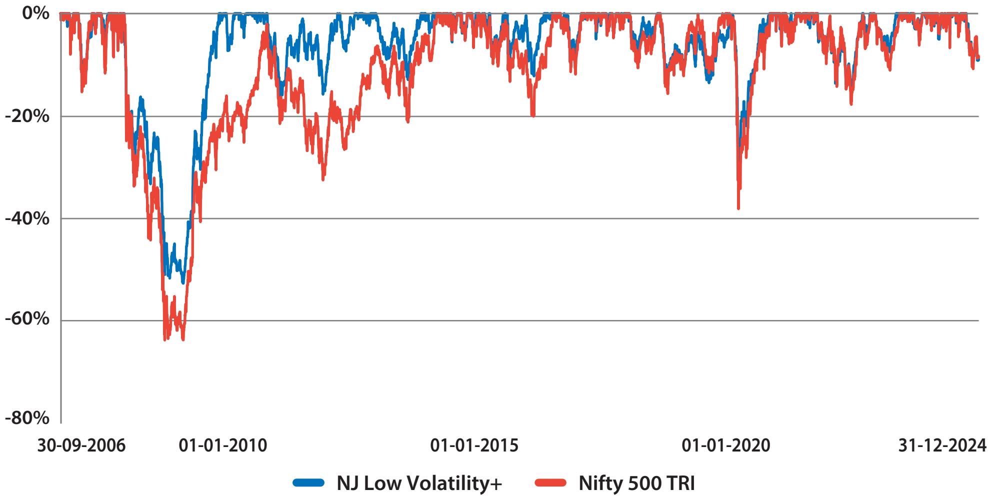
Source: Internal research, Bloomberg, CMIE, National Stock Exchange of India, NJ's Smart Beta Platform (in-house proprietary model of NJAMC). CAGRs are calculated as the average CAGR based on the rolling CAGRs (rolled daily) calculated for the respective holding periods i.e. 1, 3, 5, and 10-Yr rolling CAGRs. The period for calculation is 30th September 2006 to 31st December 2024. Past performance may or may not be sustained in future and is not an indication of future return. NJ Low Volatility+ Model is a proprietary methodology developed by NJ Asset Management Private Limited. The methodology will keep evolving with new insight based on the ongoing research and will be updated accordingly from time to time.

NJ Low Volatility+ vs Nifty 500 TRI: Return/Standard Deviation



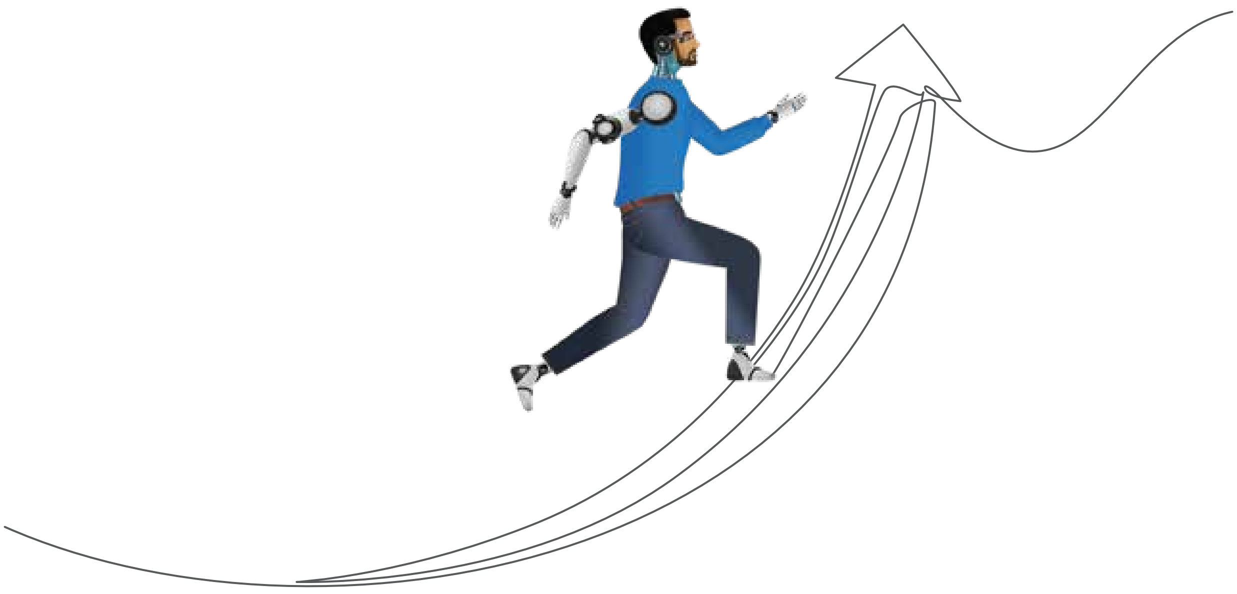
Source: Internal research, Bloomberg, CMIE, National Stock Exchange, National Stock Exchange of India, NJ's Smart Beta Platform (in-house proprietary model of NJAMC). The Return/Standard Deviation ratios have been calculated by dividing the respective rolling returns (rolled daily) by the standard deviation of the corresponding rolling returns, calculated over the period 30th September 2006 to 31st December 2024. Past performance may or may not be sustained in future and is not an indication of future return. NJ Low Volatility+ Model is a proprietary methodology developed by NJ Asset Management Private Limited. The methodology will keep evolving with new insight based on the ongoing research and will be updated accordingly from time to time.

NJ Low Volatility+ vs Nifty 500 TRI: Maximum Drawdown



	NJ Low Volatility+	Nifty 500 TRI
Maximum Drawdown	-52.63%	-63.71%

Source: Internal research, Bloomberg, CMIE, National Stock Exchange. Data analysed from 30th September 2006 to 31st December 2024. The Drawdown for a specific date has been calculated by dividing that day's NAV of NJ Low Volatility+ Model and Nifty 500 TRI by their peak NAVs up to that date, respectively. Past performance may or may not be sustained in future and is not an indication of future return. NJ Low Volatility+ Model is a proprietary methodology developed by NJ Asset Management Private Limited. The methodology will keep evolving with new insight based on the ongoing research and will be updated accordingly from time to time.



5.6 Performance of Select Low Volatility Parameters

1. Standard Deviation

Standard deviation measures the volatility or risk associated with the returns of an investment. It indicates how much a security's returns deviate from its average return over a specific period. A higher standard deviation suggests greater fluctuations in returns, implying higher risk.

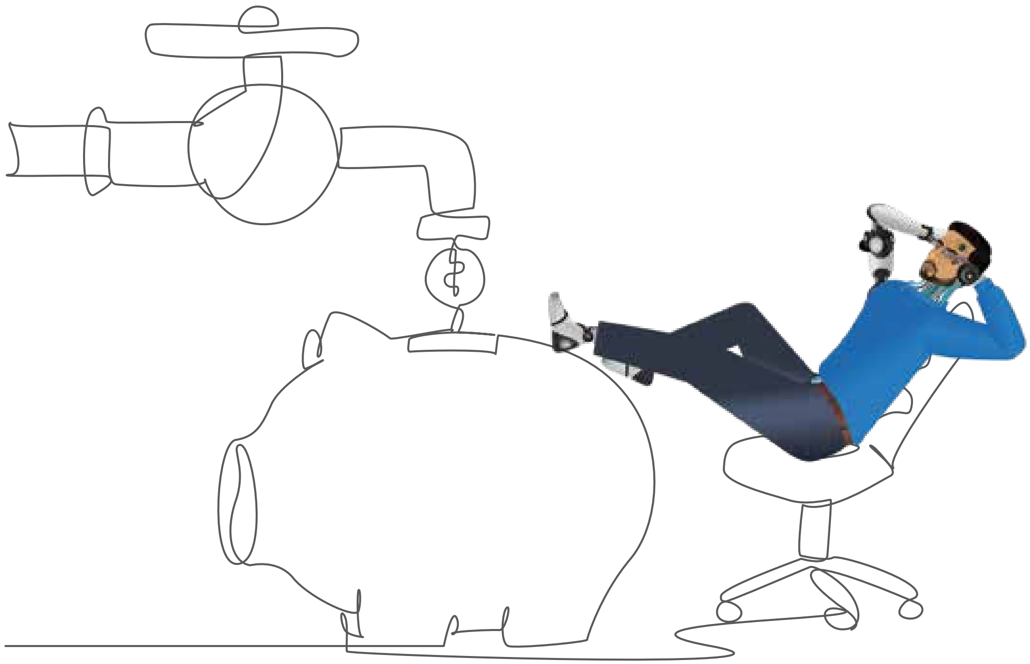
Standard deviation, also denoted as sigma (σ), is calculated as:

$$\sigma = \sqrt{\frac{\sum_{t=1}^{T}(R_t - R_{\text{avg}})^2}{T-1}}$$

Where:

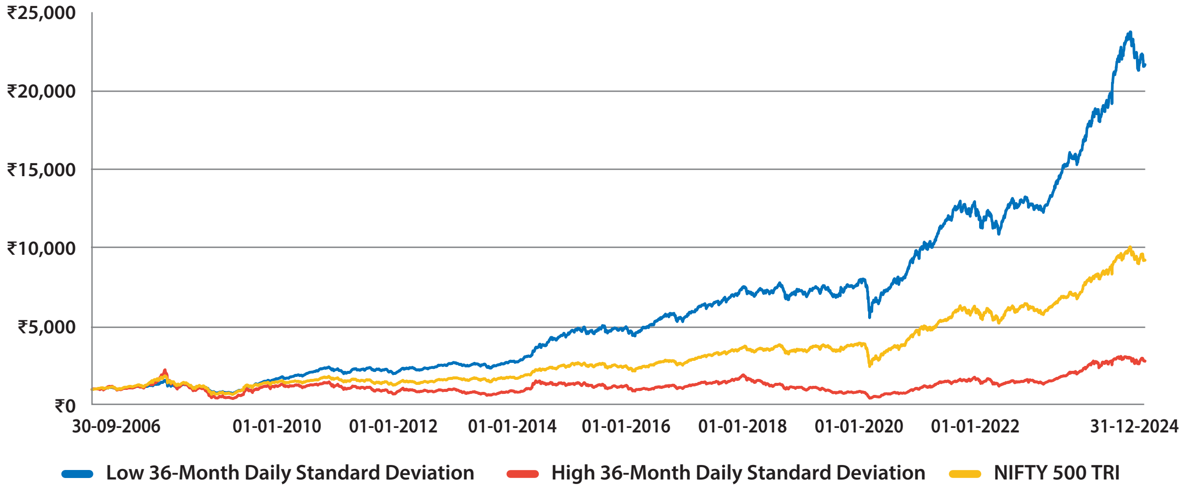
- Rt is the return of the security at time t
- R(avg) is the average return over the period
- T is the total number of return observations

For instance, if we calculate standard deviation using monthly returns over 5 years, T=60 (as there are 60 monthly return observations). Each R(t) represents the stock's return in a given month, and R(avg) is the average monthly return over the 60 months.



A standard deviation of 4% for a stock with an average return of 10% means that, on average, the stock's returns fluctuate about 4% above or below the mean return of 10%. This measure helps investors assess risk by understanding the variability of returns over time.

High Vs Low 36-Month Daily Standard Deviation



From Sep 2006 to Dec 2024	CAGR (%)	10 Year Median Rolling Returns (%)	Annualised Volatility (%)	Maximum Drawdown (%)	Cumulative Growth of 1000
Low 36-Month Daily Standard Deviation	18.33	18.32	14.53	-52.59	₹21,662
High 36-Month Daily Standard Deviation	5.83	3.11	27.69	-81.44	₹2,815
Nifty 500 TRI	12.92	13.03	20.18	-63.71	₹9,214

Source: CMIE, NJ's Smart Beta Platform. Data is for the period 30th September 2006 to 31st December 2024. "Low 36-Month Daily Standard Deviation" is the portfolio of the top 100 stocks from the Nifty 500 universe based on lowest 36-Month standard deviation of daily returns. "High 36-Month Daily Standard Deviation" is the portfolio of the bottom 100 stocks from the Nifty 500 universe based on highest 36-Month standard deviation of daily returns. Companies with less than 36-month price history are not considered. Past performance may or may not be sustained in future and is not indication of future return.

2. Beta

Beta is a measure of a security's sensitivity to market movements. It compares the volatility of a stock or portfolio to the broader market, typically represented by a benchmark index.

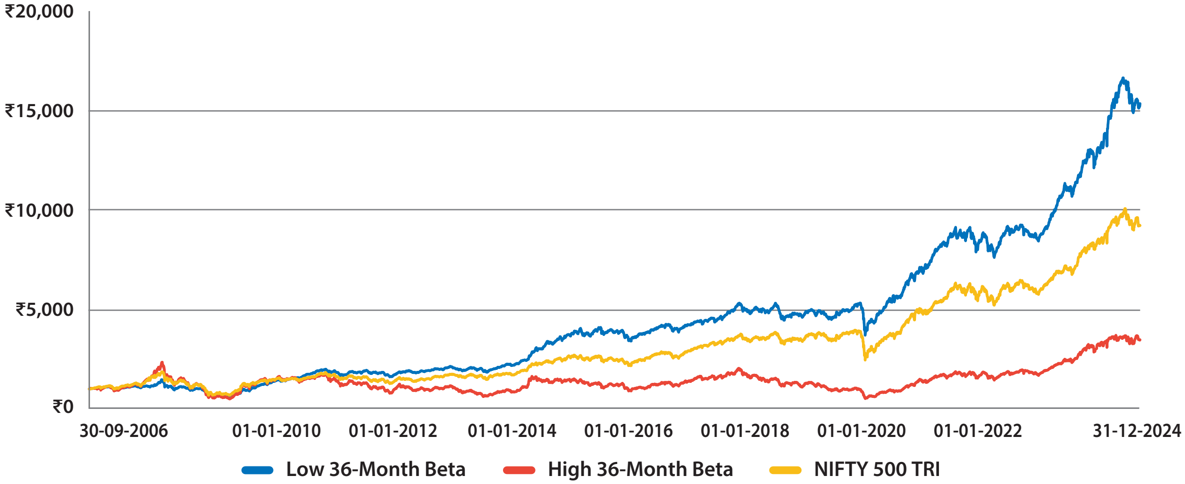
- A beta of 1 implies the stock moves in line with the market.
- A beta greater than 1 indicates higher sensitivity (more volatile than the market).
- A beta less than 1 suggests lower sensitivity (less volatile than the market).

Example:
Suppose Stock A has a beta of 1.2.

- If the market rises by 10%, Stock A is expected to rise by 12% (1.2 × 10%).
- Conversely, if the market falls by 10%, Stock A is expected to fall by 12%.

Beta helps investors assess the risk of a stock relative to market movements and its suitability in a diversified portfolio.

High Vs Low 36-Month Beta



From Sep 2006 to Dec 2024	CAGR (%)	10 Year Median Rolling Returns (%)	Annualised Volatility (%)	Maximum Drawdown (%)	Cumulative Growth of 1000
Low 36-Month Beta	16.12	16.08	13.99	-58.43	₹15,352
High 36-Month Beta	7.06	3.72	28.73	-78.80	₹3,477
Nifty 500 TRI	12.92	13.03	20.18	-63.71	₹9,214

Source: CMIE, NJ's Smart Beta Platform. Data is for the period 30th September 2006 to 31st December 2024. "Low 36-Month Beta" is the portfolio of the top 100 stocks from the Nifty 500 universe based on lowest 36-Month Beta relative to Nifty 500 index. "High 36-Month Beta" is the portfolio of the bottom 100 stocks from the Nifty 500 universe based on the highest 36-Month Beta relative to Nifty 500 index. Companies with less than 36-month price history are not considered. Past performance may or may not be sustained in future and is not indication of future return.

3. Semi Deviation

Semi-deviation measures the volatility or risk of an investment but focuses only on the negative deviations below the mean return. It is often used by risk-averse investors to assess downside risk while ignoring positive fluctuations. A higher semi-deviation indicates greater downside volatility, implying higher risk.

Semi-deviation is calculated as:

$$\text{Semi-Deviation} = \sqrt{\frac{\sum_{t=1}^{T-}(R_t - R_{\text{avg}})^2}{T-1}}$$

Where:

- R(t) = Return of the security at time t
- R(avg) = Average return over the period
- T– = Number of return observations below R(avg)
- T = Total number of return observations

For instance, if we calculate semi-deviation using monthly returns over 5 years (T=60), we only consider the months where returns were below the average return. If semi-deviation is 3% for a stock with an average return of 10%, it means that, on average, the negative returns deviate by 3% from the mean.

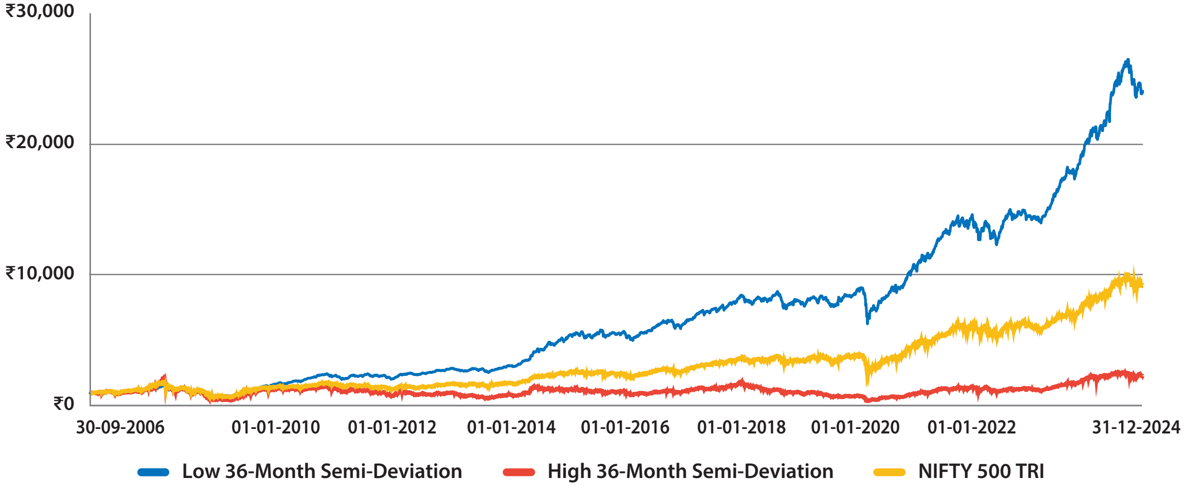
While the most common approach is to consider returns below the average return, there are other ways to compute semi-deviation based on specific risk preferences:

- Using Only Negative Returns: Instead of measuring deviations from the mean, this method considers only those return observations that are negative (i.e., losses). This is useful for investors who are concerned only with periods of absolute loss rather than relative underperformance.

- Using a Fixed Threshold: Investors may define a specific benchmark return (e.g., S&P 500 or Nifty 500) or a required minimum return (e.g., 5%). Semi-deviation is then calculated considering only the returns below this threshold, making it a more tailored measure of downside risk.

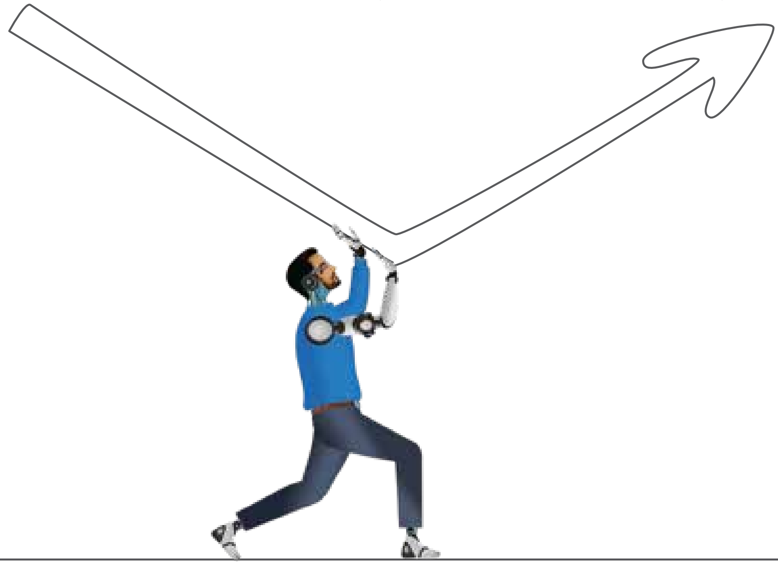
Each of these variations helps investors quantify risk in a way that aligns with their risk tolerance and investment objectives. By focusing solely on downside fluctuations, semi-deviation provides a more refined view of risk compared to standard deviation, especially for those prioritizing capital preservation.

High Vs Low 36-Month Semi-Deviation



From Sep 2006 to Dec 2024	CAGR (%)	10 Year Median Rolling Returns (%)	Annualised Volatility (%)	Maximum Drawdown (%)	Cumulative Growth of 1000
Low 36-Month Semi-Deviation	19.01	19.08	14.21	-52.82	₹24,053
High 36-Month Semi-Deviation	4.72	2.17	28.09	-81.06	₹2,815
Nifty 500 TRI	12.92	13.03	20.18	-63.71	₹9,214

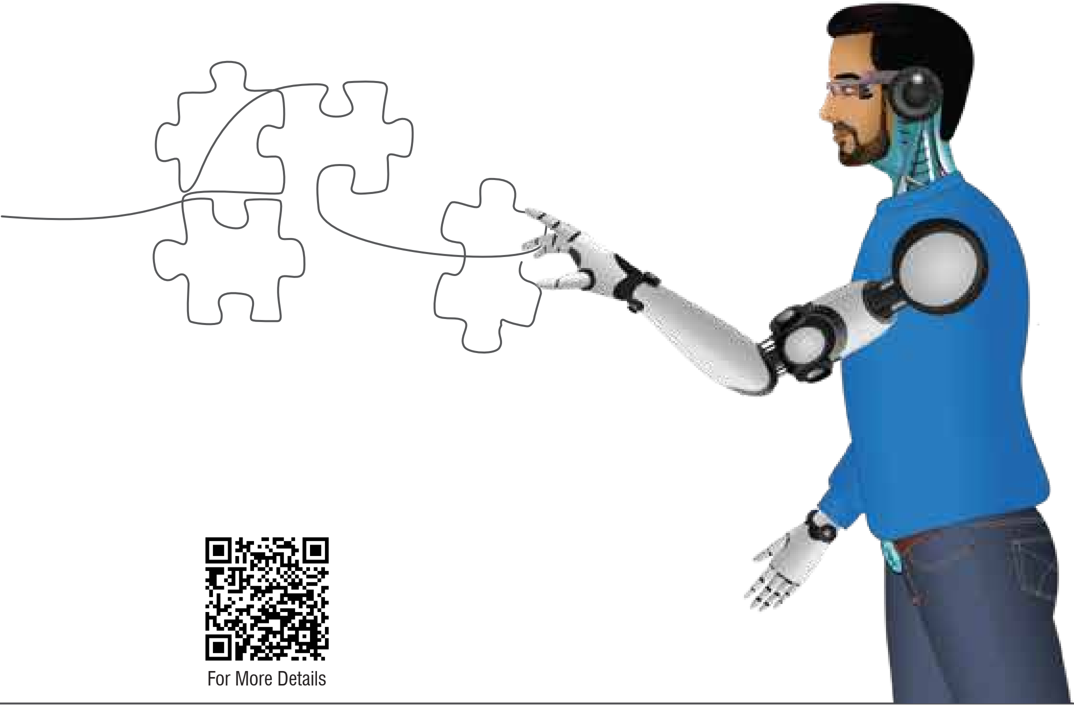
Source: CMIE, NJ's Smart Beta Platform. Data is for the period 30th September 2006 to 31st December 2024. "Low 36-Month Semi-Deviation" is the portfolio of the top 100 stocks from the Nifty 500 universe based on lowest 36-Month semi-deviation. "High 36-Month Semi-Deviation" is the portfolio of the bottom 100 stocks from the Nifty 500 universe based on the highest semi-deviation. Companies with less than 36-month price history are not considered. Past performance may or may not be sustained in future and is not indication of future return.



6. Multi-**Factor**

Diversification is the only free lunch.
-Harry Markowitz

"In the short run, the market is a voting machine. In the long run, it's a weighing machine. Diversification helps balance both."
– Warren Buffett



For More Details

6. Multi-**Factor**

A successful team in cricket is often about the composition of the team rather than the individual star player. The relationship between single factor and multi-factor strategies is no different in this regard - the team is the combination of the individual factors into one multi-factor strategy. A factor can undergo prolonged periods of underperformance with disillusioned investors running out of patience before the benefit of exposure to that factor is reaped.

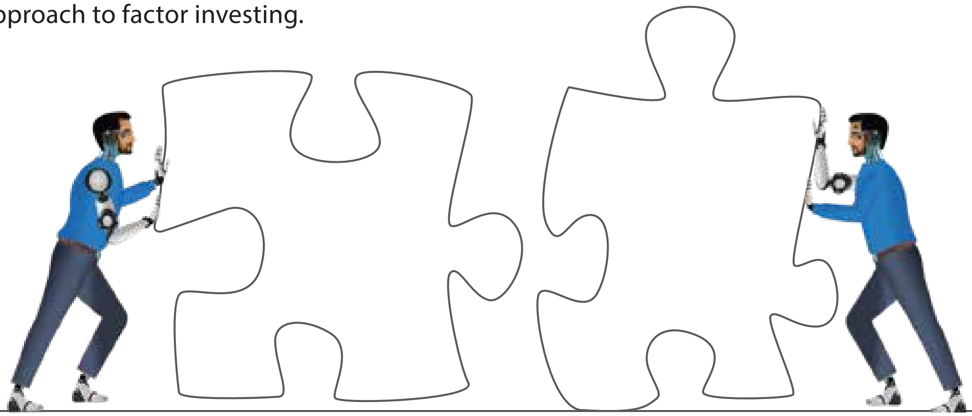
There is no right or wrong answer as to how many and which factors to include in a strategy, but all the benefits of diversification apply to factor investing as well. A multi-factor approach can offer diversification and smoothen the ride through the investment journey by harvesting multiple sources of returns.

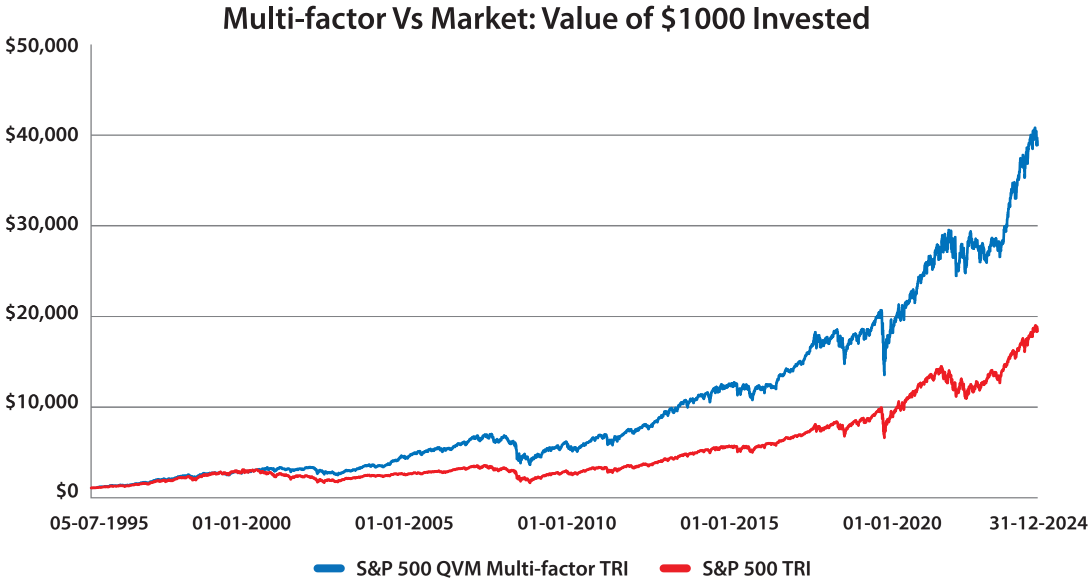
The challenge of a multi-factor portfolio is to decide how many factors to include and what approach to take. The answers can be easily found in the investor preference and objectives themselves. Investors who prioritise returns over costs may prefer a portfolio strategy dominated by momentum, while those with a strong preference for stable, consistent returns may consider low volatility to be the foundation of their portfolio. When designing a strategy for an astute investor segment with higher risk tolerance, one may consider concentrated single factor strategies to be appropriate. On the other hand, when designing a strategy for a wide variety of investors, a multi-factor strategy may serve the purpose best.

6.1 Performance of Multi-factor Models Across Markets: USA, Europe, and India

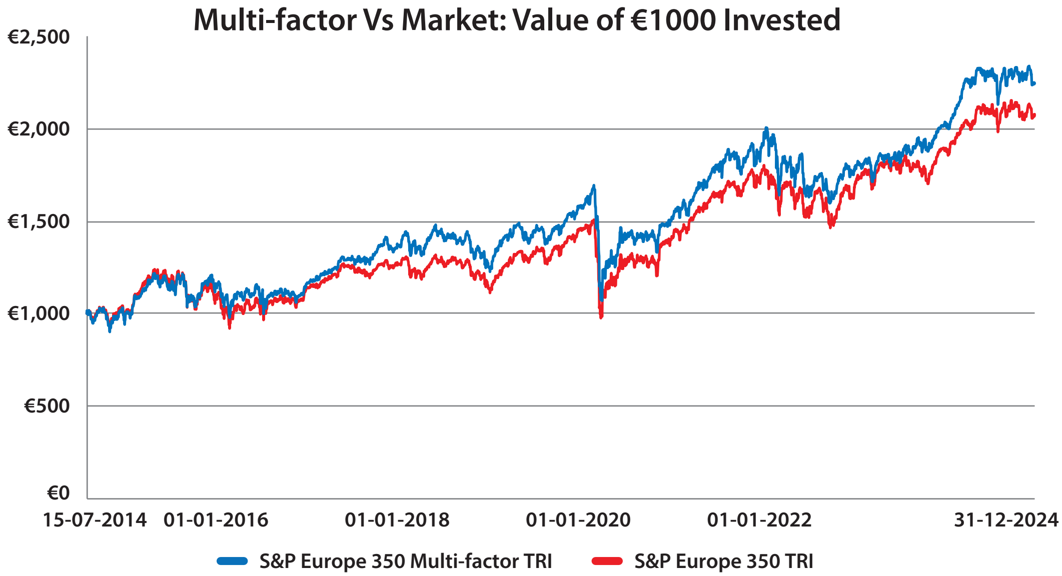
The performance of the Multi-factor index across the USA, Europe, and India highlights the effectiveness of combining multiple factors—Quality, Value, Momentum, and Low Volatility—into a single investment strategy. The historical data illustrates how the Multi-factor index has outperformed its respective benchmark over the long term, leveraging the strengths of individual factors while mitigating their cyclical downturns.

The NAV charts depict the relative growth of 1000 units of local currency investment in the Multi-factor index compared to the broad market benchmark, demonstrating its ability to generate superior risk-adjusted returns. The consistent performance of the Multi-factor strategy across different market environments underscores its robustness as a well-diversified approach to factor investing.



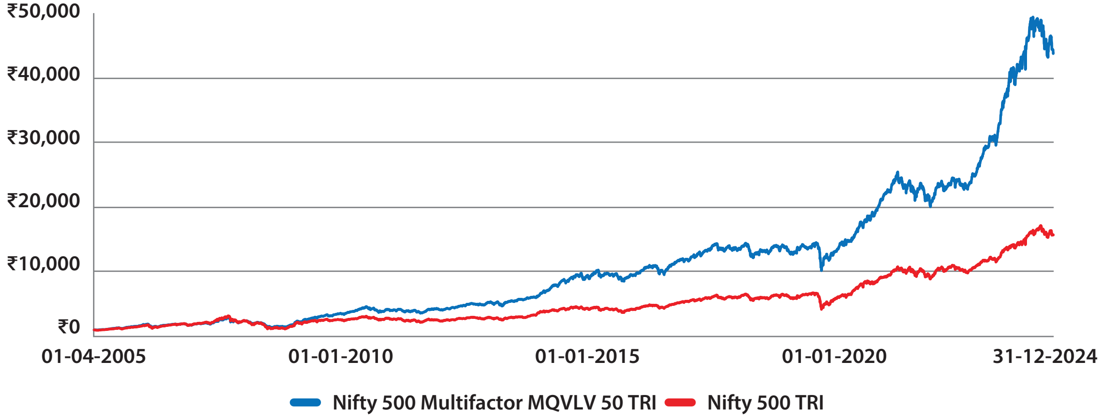


Source : Bloomberg. This chart depicts the growth in the NAV of S&P 500 QVM Multi-factor TRI vis-a-vis that of the S&P 500 TRI over the period 5th July 1995 to 31st December 2024. All the NAVs are in USD and have not been converted to INR. All the indices have been scaled to $1,000 as of 5th July 1995. Past performance may or may not be sustained in future and is not an indication of future return.



Source : Bloomberg. This chart depicts the growth in the NAV of S&P Europe 350 Multi-factor TRI vis-a-vis that of the S&P Europe 350 TRI over the period 15th July 2014 to 31st December 2024. All the NAVs are in EUR and have not been converted to INR. All the indices have been scaled to €1,000 as of 15th July 2014. Past performance may or may not be sustained in future and is not an indication of future return.

Multi-factor Vs Market: Value of ₹1000 Invested



Source : NSE. This chart depicts the growth in the NAVs of Nifty 500 Multifactor MQVLV 50 TRI vis-a-vis that of the Nifty 500 TRI over the period 1st April 2005 to 31st December 2024. All the indices have been scaled to ₹1,000 as of 1st April 2005. Past performance may or may not be sustained in future and is not an indication of future return.

Period-wise Summary of Factor Performance: Multi-factor Vs Market

Region	Period	Annualised Return (%)		3-Year Median Rolling Return (%)		10-Year Median Rolling Return (%)	
		Multi-factor	Market	Multi-factor	Market	Multi-factor	Market
USA	Jul 5, 1995 - Dec 31, 2000	23.93	19.32	24.08	25.80	-	-
	Jan 1, 2001 - Dec 31, 2006	10.35	2.94	15.25	8.98	-	-
	Jan 1, 2007 - Dec 31, 2012	5.07	2.29	1.35	1.58	-	-
	Jan 1, 2013 - Dec 31, 2018	12.23	12.15	10.37	10.90	-	-
	Jan 1, 2019 - Dec 31, 2024	16.23	16.95	13.17	10.35	-	-
	Entire Period	13.21	10.36	12.78	11.20	11.63	7.98
Europe	Jul 15, 2014 - Dec 31, 2018	5.24	2.97	7.93	3.61	-	-
	Jan 1, 2019 - Dec 31, 2024	10.20	10.55	8.71	8.99	-	-
	Entire Period	8.06	7.25	8.30	7.60	8.67	7.60
India	Apr 1, 2005 - Dec 31, 2012	23.26	14.79	20.15	8.58	-	-
	Jan 1, 2013 - Dec 31, 2018	17.48	12.75	20.34	13.11	-	-
	Jan 1, 2019 - Dec 31, 2024	21.94	17.2	25.71	19.28	-	-
	Entire Period	21.10	14.96	19.24	13.11	19.11	12.75

Source : Bloomberg, NSE. Past performance may or may not be sustained in future and is not an indication of future return. The S&P 500 QVM Multi-factor TRI, S&P Europe 350 Multi-factor TRI, & Nifty 500 Multifactor MQVLV 50 TRI are used to represent the Multi-factor index for the USA, Europe and India regions respectively. The S&P 500 TRI, S&P Europe 350 TRI, & Nifty 500 TRI are used to represent the Market index for the USA, Europe and India regions respectively.

6.2 Single Factor and Multi-Factor Models: An Analysis of Their Risks and Benefits

Factor investing stands as a cornerstone methodology in the sphere of portfolio management, where the selection of securities is guided by identifiable and quantifiable characteristics—referred to as factors—that are empirically linked to potential excess returns. These factors, among which value, size, momentum, quality, and volatility are most prominent, serve as the bedrock for constructing investment strategies that aim to achieve superior risk-adjusted performance compared to the broader market benchmarks.

Single factor models are strategies that concentrate on exploiting the return potential of one specific factor. The advantage of such a focused approach lies in its clarity and ease of implementation where investors can distinctly attribute the performance of their portfolio to the behavior of the selected factor. Moreover, the simplicity inherent in single factor models allows for straightforward attribution analysis and rebalancing procedures. However, these models are not without their limitations. The reliance on a singular factor exposes the investor to a heightened degree of cyclical risk, whereby the factor may exhibit varying degrees of performance through different economic phases. This can potentially lead to periods of significant underperformance. Furthermore, such models harbor concentration risks, as the portfolio may be unduly exposed to sector-specific shocks or macroeconomic trends that disproportionately affect the chosen factor.

In contrast, multi-factor models present a more nuanced and sophisticated investment strategy. By combining various factors, the multi-factor models strive to construct a portfolio that captures a more comprehensive set of factor risk premiums, potentially leading to a more consistent and stable performance over time. The diversification achieved through the combination of low-correlated factors reduces overall portfolio volatility, thereby offering a smoother investment journey. Nonetheless, the intricate nature of multi-factor models introduces complexity to the investment process. The risk of overfitting, a scenario where a model is excessively tailored to historical data, thus impairing its future predictive power is a pertinent concern. Additionally, the interplay between different factors may lead to a dilution effect, where the strong performance of one factor is offset by the weaker performance of another, potentially muting the overall return profile of the portfolio.

10-YEAR FACTOR CORRELATIONS ACROSS MARKETS: USA

Factors	S&P 500 Quality	S&P 500 Enhanced Value	S&P 500 Momentum	S&P 500 Low Volatility
S&P 500 Quality	**1.00**	**-0.29**	**0.17**	**0.39**
S&P 500 Enhanced Value	**-0.29**	**1.00**	**-0.45**	**-0.16**
S&P 500 Momentum	**0.17**	**-0.45**	**1.00**	**0.05**
S&P 500 Low Volatility	**0.39**	**-0.16**	**0.05**	**1.00**

Source: Bloomberg. The correlations mentioned above are the average of daily rolling 10-year correlation for the period starting from 05 July 1995 to 31 December 2024. The correlations are calculated using the daily excess return over the S&P 500 Total Return Index.

10-YEAR FACTOR CORRELATIONS ACROSS MARKETS: EUROPE				
Factors	**S&P Europe 350 Quality**	**S&P Europe 350 Enhanced Value**	**S&P Europe 350 Momentum**	**S&P Europe 350 Low Volatility**
S&P Europe 350 Quality	**1.00**	**-0.48**	**0.37**	**0.37**
S&P Europe 350 Enhanced Value	**-0.48**	**1.00**	**-0.43**	**-0.51**
S&P Europe 350 Momentum	**0.37**	**-0.43**	**1.00**	**0.31**
S&P Europe 350 Low Volatility	**0.37**	**-0.51**	**0.31**	**1.00**

Source: Bloomberg. The correlations mentioned above are the average of daily rolling 10-year correlation for the period starting from 15 July 2014 to 31 December 2024. The correlations are calculated using the daily excess return over the S&P Europe 350 Total Return Index.

10-YEAR FACTOR CORRELATIONS ACROSS MARKETS: INDIA					
Factors	**NJ Quality+**	**NJ Enhanced Value**	**NJ Traditional Value**	**NJ Momentum+**	**NJ Low Volatility+**
NJ Quality+	**1.00**	**0.77**	**0.59**	**0.72**	**0.83**
NJ Enhanced Value	**0.77**	**1.00**	**0.74**	**0.70**	**0.62**
NJ Traditional Value	**0.59**	**0.74**	**1.00**	**0.60**	**0.39**
NJ Momentum+	**0.72**	**0.70**	**0.60**	**1.00**	**0.61**
NJ Low Volatility+	**0.83**	**0.62**	**0.39**	**0.61**	**1.00**

Source: Internal research, CMIE, National Stock Exchange of India, NJ's Smart Beta Platform (in-house proprietary model of NJAMC). The correlations mentioned above are the average of daily rolling 10-year correlation for the period starting from 30 September 2006 to 31 December 2024. The correlations are calculated using the daily excess return over the Nifty 500 total return index.

6.3 Factor Cyclicality: Understanding the Shifts

Factor investing thrives on the concept that factors tend to outperform the broader market during different economic phases. These phases, in turn, can be influenced by broader macroeconomic conditions such as interest rates, inflation, GDP growth, and geopolitical events. Factor cyclicality refers to the tendency of different factors to perform better or worse depending on these changing economic conditions.

For instance, momentum tends to thrive during expansions, while low volatility and quality outperform in downturns. Understanding factor cyclicality is crucial for optimising portfolios by aligning factors with the prevailing economic environment.

Factor Cyclicality in the Indian Context

Academic studies and real-world evidence support the idea that factor cyclicality is an important consideration. Research by academics such as Fama and French (1993) on the three-factor model, has highlighted that factor performance varies over time, influenced by broader economic and market cycles. Their findings emphasize the role of multifactor strategies in diversifying across multiple factors to improve risk-adjusted returns and reduce exposure to any single factor's inherent volatility.

The application of factor investing in emerging markets like India comes with its own unique set of challenges, largely due to the differences in market microstructure, data availability, and liquidity compared to developed markets. Nonetheless, Indian market research has revealed the behaviour of different factors through varying economic cycles.

Dynamic Adjustments for Optimal Returns

Bijoy and Kedia (2023) underscore the importance of adapting factor strategies to prevailing market conditions. Their study found that factors like trading volume, dividend yield, and long-term volatility significantly impact abnormal returns. Dynamic adjustments to factor exposures, rather than static strategies, can lead to better performance by leveraging current market opportunities.

Understanding Market Cyclicality

A working paper from the Madras School of Economics highlights the critical role of understanding market cyclicality. The research emphasises that market participants' behaviour shifts across economic cycles, influencing factor performance. Recognizing these shifts helps investors anticipate changes and refine their strategies to stay ahead of market dynamics.

These findings highlight the cyclical nature of factor performance, underscoring the importance of managing factor exposure based on the prevailing economic environment to enhance risk-adjusted returns in the Indian market. The unique nature of the Indian stock market, as shown in these studies, calls for tailored factor strategies.

The table below shows the historical calendar year performance of various factors:

Factor	2006*	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024*
NJ Quality +	3.04	50.12	-52.39	114.47	33.43	-15.82	33.14	6.34	60.27	11.42	7.46	42.24	-2.32	2.92	24.85	49.62	4.51	56.67	28.18
NJ Enhanced Value	9.12	58.94	-60.87	122.88	25.36	-28.80	38.01	1.50	66.04	10.84	3.18	48.49	-13.97	-0.06	23.46	48.03	3.17	35.28	19.14
NJ Traditional Value	2.07	76.79	-64.28	160.38	30.81	-32.51	35.37	-10.74	72.35	5.87	16.88	48.22	-19.97	-13.33	14.80	53.67	10.70	56.57	27.20
NJ Momentum+	12.98	89.56	-58.68	96.74	28.92	-17.03	43.71	3.00	81.74	15.22	0.22	69.43	-7.92	9.16	37.75	55.99	6.75	47.78	32.17
NJ Low Volatility+	7.13	37.75	-46.47	98.97	34.53	-10.72	31.86	5.83	60.72	10.65	10.53	36.43	0.27	2.17	17.84	31.65	3.60	38.59	21.47
Nifty 500 TRI	10.55	64.58	-56.78	85.67	15.27	-26.40	33.48	3.89	39.12	0.04	4.68	37.65	-1.55	8.64	17.70	30.95	4.25	26.91	16.00

*Does not represent a complete calendar year. | Past performance may or may not sustain in future.

Factor Cyclicality During Major Economic Events

The analysis of factor performance during significant economic crises, such as the Global Financial Crisis (GFC) and the COVID-19 pandemic, reveals distinct patterns across different investment factors and regions. By comparing performance across three periods i.e. pre-crisis, during the crisis, and post-crisis, we can understand the cyclicality of factors and their resilience.

India

Global Financial Crisis

COMPARATIVE ANALYSIS OF FACTOR PERFORMANCE DURING GLOBAL FINANCIAL CRISIS (GFC)			
Portfolio Returns	Pre GFC Bull-Period (30/09/2006 to 31/12/2007)	GFC Correction (01/01/2008 to 31/03/2009)	Post GFC Recovery (01/04/2009 to 31/12/2010)
NJ Quality+	54.67%	-53.87%	197.47%
NJ Momentum+	114.17%	-59.77%	163.90%
NJ Low Volatility+	47.57%	-46.29%	170.94%
NJ Enhanced Value	73.43%	-63.16%	196.78%
NJ Traditional Value	80.45%	-65.45%	250.88%
NJ Multi Factor+	68.63%	-51.66%	168.66%
Nifty 500 - TRI	82.15%	-56.67%	116.72%

Source: Internal research, CMIE, NJ's Smart Beta Platform (in-house proprietary model of NJAMC). Calculations are for the specific periods mentioned in the respective column. NJ Quality+, NJ Momentum+, NJ Low Volatility+, NJ Traditional Value, NJ Enhanced Value and NJ Multi Factor+ are in-house proprietary methodologies developed by NJ Asset Management Private Limited. The methodologies will keep evolving with new insights based on the ongoing research and will be updated accordingly from time to time. Past performance may or may not be sustained in the future and is not an indication of future return. The above is only for illustration purposes and should not be construed as indicative return of offering of NJ Asset Management Private Limited.

Covid-19 Pandemic

COMPARATIVE ANALYSIS OF FACTOR PERFORMANCE DURING COVID-19 PANDEMIC			
Portfolio Returns	Pre Pandemic Period (01/01/2019 to 31/12/2019)	During Pandemic Period (01/01/2020 to 23/03/2020)	Post Pandemic Period (24/03/2020 to 31/12/2021)
NJ Quality+	2.92%	-33.47%	179.90%
NJ Momentum+	9.16%	-30.75%	208.87%
NJ Low Volatility+	2.17%	-30.00%	120.19%
NJ Enhanced Value	-0.06%	-39.28%	202.92%
NJ Traditional Value	-13.33%	-43.50%	217.70%
NJ Multi Factor+	-1.74%	-32.74%	166.51%
Nifty 500 - TRI	8.64%	-36.67%	139.79%

Source: Internal research, CMIE, NJ's Smart Beta Platform (in-house proprietary model of NJAMC). Calculations are for the specific periods mentioned in the respective column. NJ Quality+, NJ Momentum+, NJ Low Volatility+, NJ Traditional Value, NJ Enhanced Value and NJ Multi Factor+ are in-house proprietary methodologies developed by NJ Asset Management Private Limited. The methodologies will keep evolving with new insights based on the ongoing research and will be updated accordingly from time to time. All the indices have been scaled to ₹1,000 as of 30th September 2006. Past performance may or may not be sustained in the future and is not an indication of future return. The above is only for illustration purposes and should not be construed as indicative return of offering of NJ Asset Management Private Limited.

USA

Global Financial Crisis

COMPARATIVE ANALYSIS OF FACTOR PERFORMANCE DURING GLOBAL FINANCIAL CRISIS (GFC)			
Portfolio Returns	Pre GFC Bull-Period (30/09/2006 to 31/12/2007)	GFC Correction (01/01/2008 to 31/03/2009)	Post GFC Recovery (01/04/2009 to 31/12/2010)
S&P 500 Quality TRI	24.43%	-37.50%	55.82%
S&P 500 Enhanced Value TRI	5.72%	-58.62%	95.23%
S&P 500 Momentum TRI	16.47%	-37.98%	45.92%
S&P 500 Low Volatility TRI	6.85%	-28.50%	47.71%
S&P 500 QVM Multi-factor TRI	26.96%	-39.99%	44.99%
S&P 500 TRI	12.56%	-43.94%	60.83%

Source: Internal research, Bloomberg. Calculations are for the specific periods mentioned in the respective column. Past performance may or may not be sustained in the future and is not an indication of future return. The above is only for illustration purposes and should not be construed as indicative return of offering of NJ Asset Management Private Limited.

Covid-19 Pandemic

COMPARATIVE ANALYSIS OF FACTOR PERFORMANCE DURING COVID-19 PANDEMIC			
Portfolio Returns	Pre Pandemic Period (01/01/2019 to 31/12/2019)	During Pandemic Period (01/01/2020 to 23/03/2020)	Post Pandemic Period (24/03/2020 to 31/12/2021)
S&P 500 Quality TRI	33.91%	-28.88%	92.72%
S&P 500 Enhanced Value TRI	29.22%	-47.88%	107.62%
S&P 500 Momentum TRI	26.25%	-26.15%	93.80%
S&P 500 Low Volatility TRI	28.26%	-31.90%	64.99%
S&P 500 QVM Multi-factor TRI	26.18%	-32.31%	84.68%
S&P 500 TRI	31.49%	-30.43%	100.22%

Source: Internal research, Bloomberg. Calculations are for the specific periods mentioned in the respective column. Past performance may or may not be sustained in the future and is not an indication of future return. The above is only for illustration purposes and should not be construed as indicative return of offering of NJ Asset Management Private Limited.

Europe

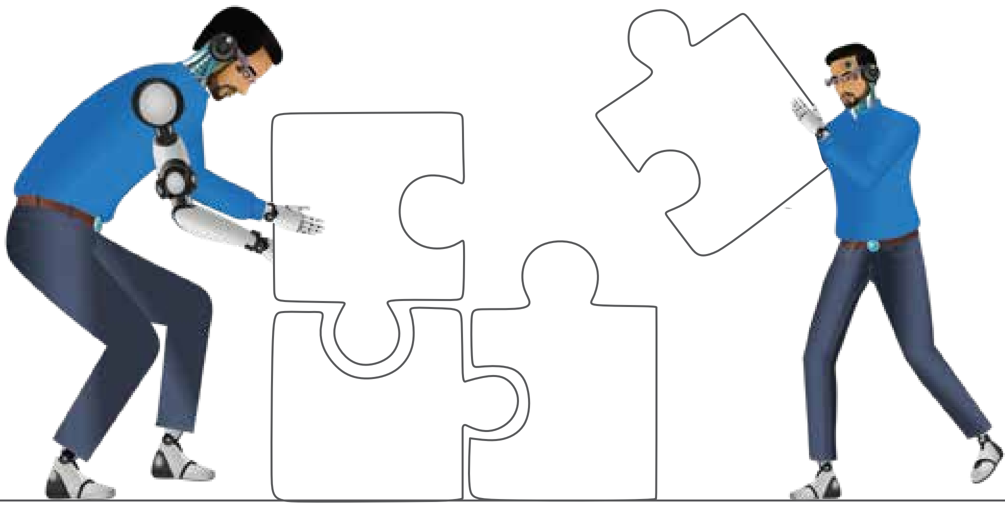
Covid-19 Pandemic

COMPARATIVE ANALYSIS OF FACTOR PERFORMANCE DURING COVID-19 PANDEMIC			
Portfolio Returns	Pre Pandemic Period (01/01/2019 to 31/12/2019)	During Pandemic Period (01/01/2020 to 23/03/2020)	Post Pandemic Period (24/03/2020 to 31/12/2021)
S&P Europe 350 Quality TRI	35.34%	-31.37%	73.92%
S&P Europe 350 Enhanced Value TRI	20.46%	-48.05%	96.54%
S&P Europe 350 Momentum TRI	31.88%	-24.84%	67.49%
S&P Europe 350 Low Volatility TRI	26.84%	-27.69%	52.99%
S&P Europe 350 QVM Multi-factor TRI	31.49%	-30.43%	100.22%
S&P Europe 350 TRI	27.24%	-32.16%	66.48%

Source: Internal research, Bloomberg. Calculations are for the specific periods mentioned in the respective column. Past performance may or may not be sustained in the future and is not an indication of future return. The above is only for illustration purposes and should not be construed as indicative return of offering of NJ Asset Management Private Limited.

The comparison of factor performance during the COVID-19 pandemic and the Global Financial Crisis reiterates the importance of factor cyclicality in building a robust portfolio. While single-factor strategies can perform exceptionally well during certain market phases, their reliance on a singular factor exposes investors to concentrated risks.

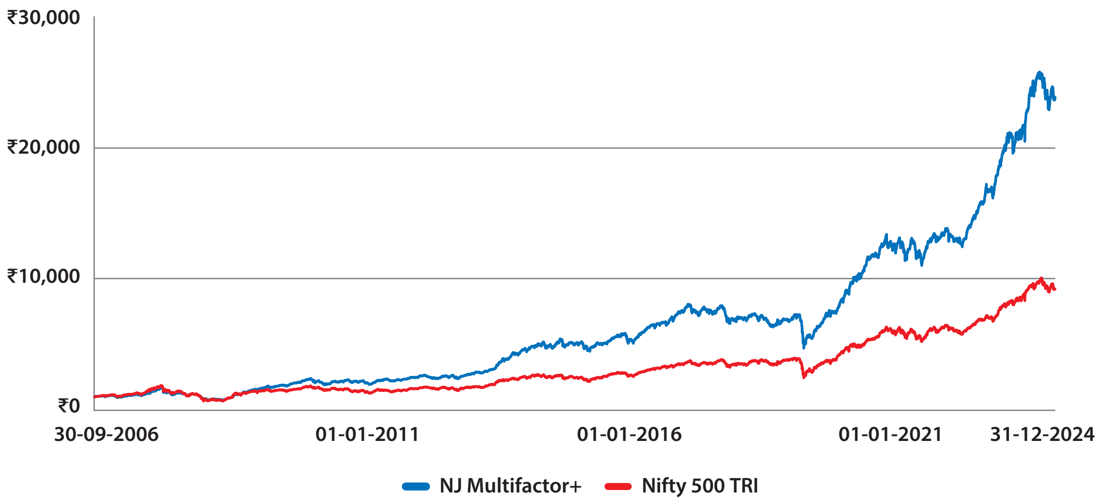
On the other hand, multifactor strategies provide diversification across factors, allowing investors to capture different risk premiums and achieve more stable returns over time. By understanding factor cyclicality and adjusting factor exposures based on macroeconomic conditions, investors can enhance their portfolios and reduce the impact of economic fluctuations.



6.4 NJ Multifactor+ Model

NJ Multifactor+ Model is created by combining all the four single factor models and equally allocating among all. The weights are rebalanced on a half yearly basis.

Value of ₹1000 Invested

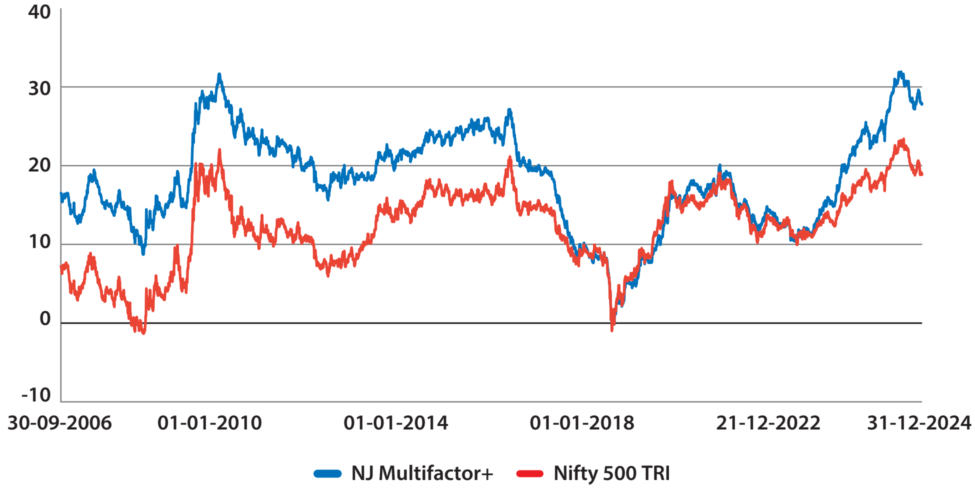


Source: Internal research, Bloomberg, CMIE, National Stock Exchange, NJ's Smart Beta Platform (in-house proprietary model of NJAMC). Calculations are for the period 30th September 2006 to 31st December 2024. NJ Multifactor+ Model is an in-house proprietary methodology developed by NJ Asset Management Private Limited. The methodology will keep evolving with new insight based on the ongoing research and will be updated accordingly from time to time. Past performance may or may not be sustained in future and is not an indication of future return. The above is only for illustration purposes and should not be construed as indicative return of offering of NJ Asset Management Private Limited.

	10-Year Median Rolling Return (%)	10-Year Rolling Volatility (%)	Return-to-Risk Ratio (x)	Drawdown (%)
NJ Multifactor+	18.67	4.66	4.01	-57.56
Nifty 500 TRI	13.04	5.60	2.33	-63.71

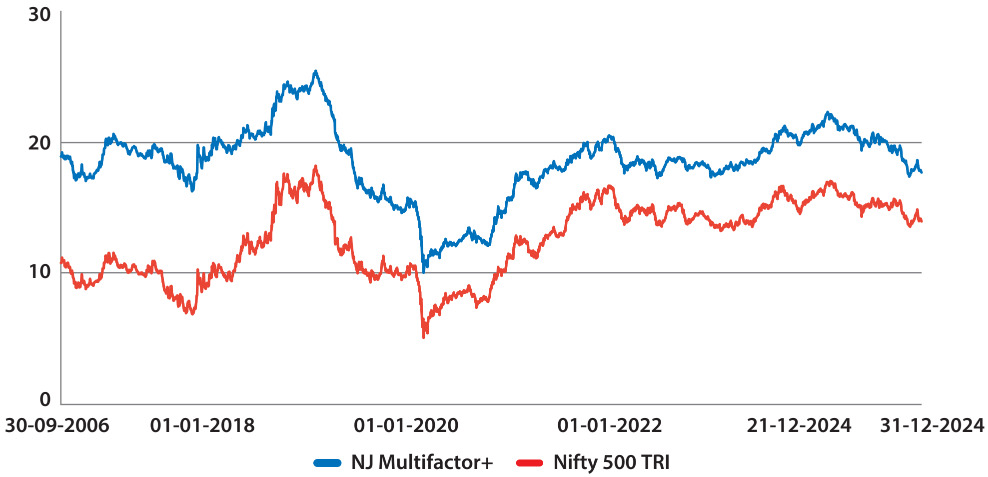
Source: Internal research, Bloomberg, National Stock Exchange, NJ's Smart Beta Platform (in-house proprietary model of NJAMC). Calculations are for the period 30th September 2006 to 31st December 2024. NJ Multifactor+ Model is an in-house proprietary methodology developed by NJ Asset Management Private Limited. The methodology will keep evolving with new insight based on the ongoing research and will be updated accordingly from time to time. Past performance may or may not be sustained in future and is not an indication of future return. The above is only for illustration purposes and should not be construed as indicative return of offering of NJ Asset Management Private Limited.

NJ Multifactor+ vs Nifty 500 TRI : 5-Yr Rolling Returns



Source: Internal research, Bloomberg, CMIE, National Stock Exchange of India, NJ's Smart Beta Platform (in-house proprietary model of NJAMC). 5-Yr CAGRs are calculated for the period 30th September 2006 to 31st December 2024 and have been rolled on a daily basis. Past performance may or may not be sustained in future and is not indication of future return. NJ Multifactor+ Model is a proprietary methodology developed by NJ Asset Management Private Limited. The methodology will keep evolving with new insight based on the ongoing research and will be updated accordingly from time to time.

NJ Multifactor+ vs Nifty 500 TRI : 10-Yr Rolling Returns

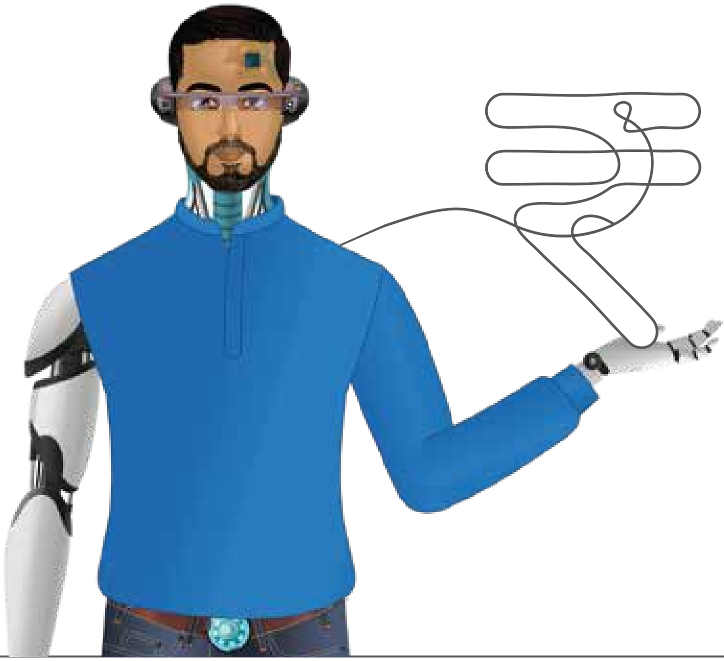


Source: Internal research, Bloomberg, CMIE, National Stock Exchange of India, NJ's Smart Beta Platform (in-house proprietary model of NJAMC). 10-Yr CAGRs are calculated for the period 30th September 2006 to 31st December 2024 and have been rolled on a daily basis. Past performance may or may not be sustained in future and is not indication of future return. NJ Multifactor+ Model is a proprietary methodology developed by NJ Asset Management Private Limited. The methodology will keep evolving with new insight based on the ongoing research and will be updated accordingly from time to time.

7. Forensic and **Governance**

"Good governance is the foundation of sustainable wealth creation."
-N. R. Narayana Murthy

"Accounting is the language of business, but forensic analysis is how you read between the lines."
– Howard Schilit



For More Details

7. Forensic and **Governance**

7.1 Forensic and Governance: Unmasking the Red Flags Quantitatively

Some financial statements can change their appearance, much like a chameleon blending into its surroundings. With a few tweaks or creative metrics, even losses can look less concerning. Take WeWork's* "Community-Adjusted EBITDA" as an example, it was like labelling junk food as healthy. However, forensic analysis is like a predator that uncovers the truth, and strong governance ensures companies can't hide their flaws forever. Research consistently shows that businesses with solid corporate governance are better managed, more sustainable, and ultimately more valuable.

*Note: The above should not be construed as a recommendation to buy/sell any stocks specified above. The above content is based on the internal research process. The AMC may or may not hold the above stock in its portfolio. Investors should consult their own advisors, and tax consultants before making any decision.

7.2 Understanding Forensic and Governance Analysis

Forensic analysis involves a detailed evaluation of a company's financial statements to detect red flags that could indicate accounting fraud or irregularities. This step is pivotal in identifying and avoiding potential accounting frauds well in advance, safeguarding investors from sudden losses. The study "Contribution of Forensic Accounting to Corporate Governance" by Bhasin (2013) underscores the effectiveness of such techniques in identifying financial irregularities and preventing corporate fraud.

Governance analysis focuses on the ethical standards and management practices that shape a company's direction. A company with strong governance practices ensures transparency, accountability, and alignment of interests between management and shareholders. Research like "The Impact of Corporate Governance on Firm Performance" by Gompers, Ishii, and Metrick (2003) demonstrates how firms with robust governance outperform their peers in profitability and valuation.

7.3 The Rise of Forensic & Governance in Investing

Corporate governance and forensic analysis have taken centre stage in the investment world, driven by scandals like Enron in 2001 and Satyam in India. These events exposed how weak oversight and financial manipulation can devastate markets. Enron's concealment of debt caused shareholder losses of over $74 billion, while Satyam's inflated profits led to a 70% stock drop in a single day. Such incidents reshaped investment strategies, prioritizing governance and forensic checks.

Financial statements, once trusted, can be manipulated, making deeper scrutiny essential. In India, governance issues like accounting fraud and capital misallocation are widespread, with 40% of BSE 500 companies exiting the index over a decade, as per Marcellus. Research also highlights financial red flags as indicators of manipulation, emphasizing the need for robust analysis.

Strong governance fosters transparency and stability, enabling informed decisions and reducing risks. Forensic analysis adds value by detecting unusual profit margins, cash flow issues, and governance lapses. Red flags like abrupt auditor resignations or policy changes signal deeper problems.

Forensic and governance analyses are now indispensable, helping investors identify risks, address red flags, and make confident, data-driven decisions.

7.4 Role of Forensic and Governance Analysis in Factor Investing

Factor investing is fundamentally a data-driven strategy that identifies securities with specific characteristics likely to drive returns. It depends heavily on quantitative data. However, the reliability of these strategies hinges on the quality of the underlying data. The entire investment strategy can collapse if the data is compromised due to poor governance, fraudulent reporting, or manipulation.

This is where forensic and governance analysis becomes indispensable in fortifying factor-based models. While factor investing traditionally leans on quantitative data, forensic and governance analysis often involves qualitative dimensions, such as assessing management integrity, and governance policies, or identifying red flags in corporate behaviour. Bridging this gap between quantitative and qualitative measures is challenging, but it is critical for building robust factor models.

A notable example is Yes Bank*, which once appeared attractive in traditional factor models due to high growth and profitability metrics. However, deeper forensic insights, such as aggressive lending practices, poor governance, and questionable asset quality, could have acted as early warning signals. By factoring in governance data, investors could have avoided exposure to the risks that later became evident.

At NJ AMC, we have taken on the challenge of transforming qualitative forensic and governance insights into data-driven inputs for factor investing. By embedding robust forensic and governance analysis into our models, we ensure to filter out companies with potential governance issue or financial red flags.

*Note: The above should not be construed as a recommendation to buy/sell any stocks specified above. The above content is based on the internal research process. The AMC may or may not hold the above stock in its portfolio. Investors should consult their own advisors, and tax consultants before making any decision.

7.5 NJ Mutual Fund’s Forensic & Governance Model: Quantitative Approach

NJ Mutual Fund's Forensic & Governance Model is designed to detect red flags through quantitative measures. The model identifies companies prone to:

- **Earnings Manipulation:** Detecting aggressive revenue recognition practices.
- **Hidden Liabilities:** Uncovering off-balance-sheet debts.
- **Governance Risks:** Assessing factors like promoter integrity and independence of auditors.

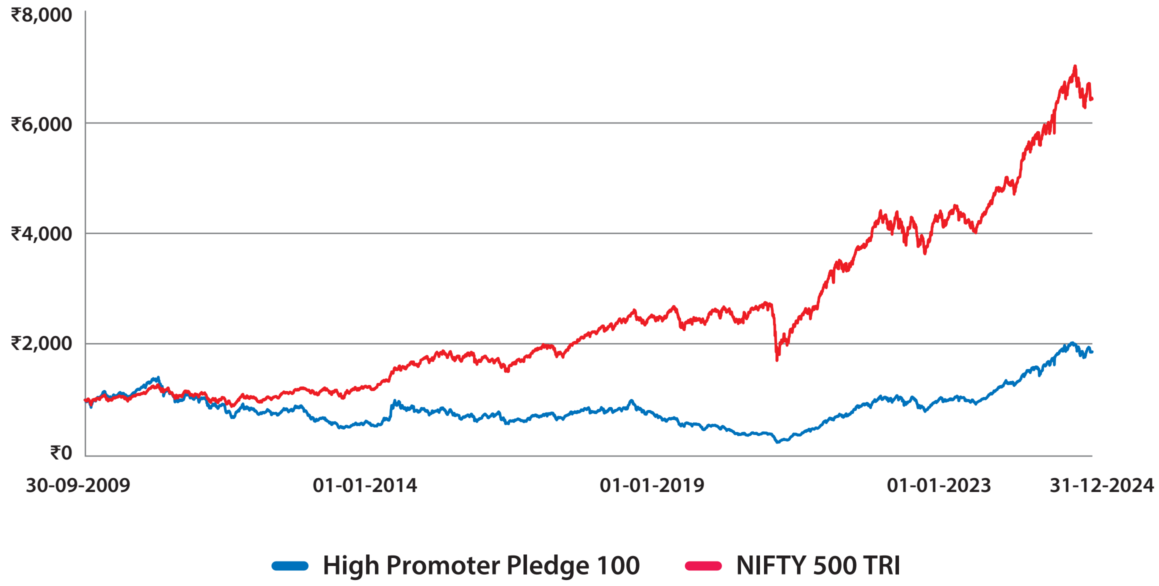
The following are a few of the parameters used to evaluate the stocks:

1) **Promoter Pledge:** This measures the percentage of promoters' shares pledged as collateral.

Company	Promoter Pledge (%)
A	5%
B	40%

Company A, with a 5% promoter pledge, is considered to have lower governance risk compared to Company B, which has a 40% pledge. A higher pledge ratio in Company B may signal that the promoters are financially stretched, which could lead to potential conflicts of interest or liquidity concerns. High pledging may also lead to forced share sales, impacting stock price stability. This makes Company A relatively less risky in terms of the promoters' integrity and alignment of interests with minority shareholders.

NIFTY 500 TRI VS High Promoter Pledge



From Sep 2009 to Dec 2024	CAGR (%)	10 Year Median Rolling Returns (%	Annualised Volatility (%)	3-Year Minimum Rolling Return (%)	3-Year Probability of Loss (%)
High Promoter Pledge 100	4.19	1.86	22.37	-33.76	55.53
Nifty 500 TRI	12.96	14.16	16.22	-6.31	4.22

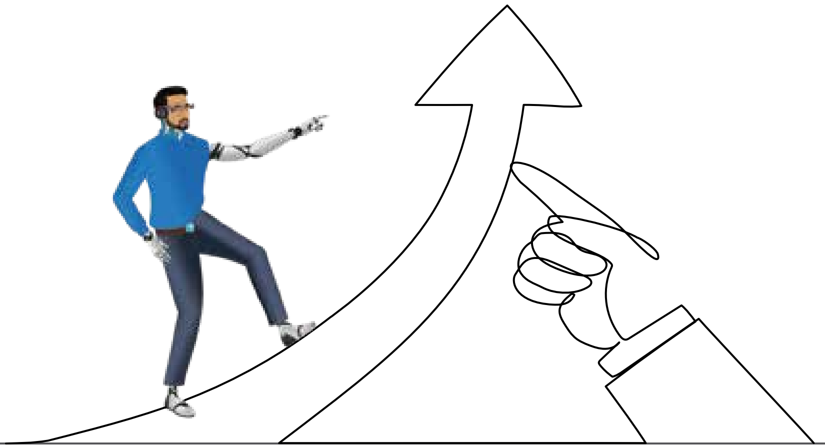
Worst 5 Drawdowns	Drawdown of High Promoter Pledge Portfolio	Drawdown of Nifty 500	Drawdown Date	Recovery Time (Days) for High Promoter Pledge Portfolio	Recovery Time (Days) for Nifty 500
1	-42.37%	-38.11%	23-03-2020	140	228
2	-51.47%	-31.06%	20-12-2011	4,368	808
3	-33.18%	-20.06%	25-02-2016	446	148
4	-26.47%	-17.77%	20-06-2022	351	148
5	-23.68%	-15.64%	26-10-2018	836	398

Source: CMIE, NJ's Smart Beta Platform. Data from September 30, 2009, to December 31, 2024. The High Promoter Pledge portfolio consists of companies that rank in the bottom Decile (Bottom 10%) based on the promoter pledge parameter. Probability of Loss (%) is calculated by dividing the number of negative observations by total number of observations. Past performance may or may not be sustained in the future and is not an indication of future returns.

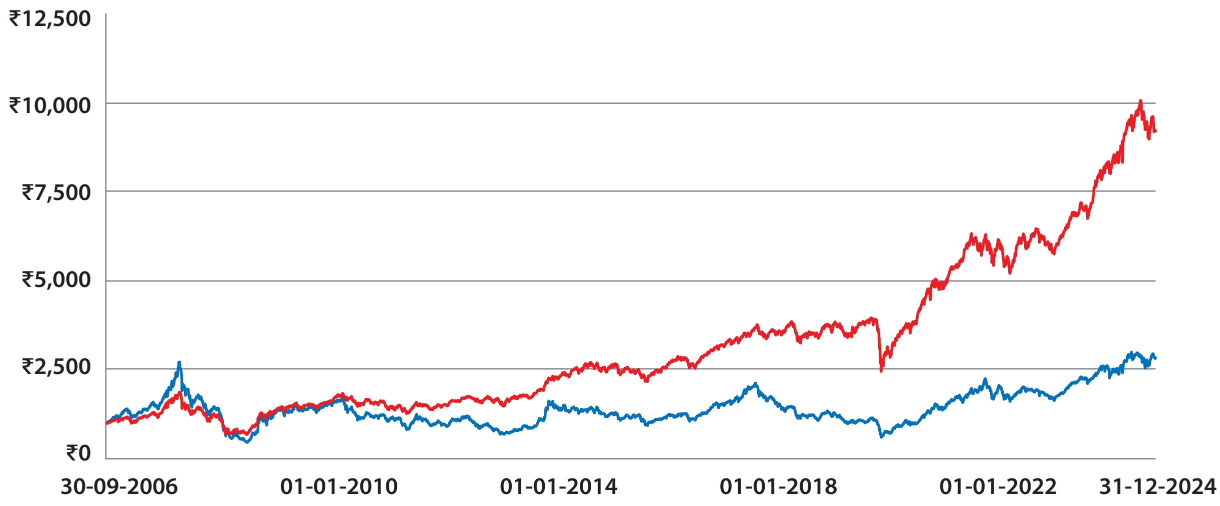
2) Operating Cash Flow to EBITDA: This ratio compares the actual cash generated from operations to earnings before interest, taxes, depreciation, and amortization. A significant discrepancy may suggest earnings manipulation such as aggressive revenue recognition by inflating receivables, channel stuffing and over-invoicing, and inventory manipulation. As a thumb rule, a ratio between 80% to 200% of EBITDA is generally considered as healthy.

Company	Operating Cash Flow to EBITDA (%
X	80%
Y	20%

Company X, with an 80% operating cash flow to EBITDA ratio, demonstrates robust cash generation that aligns with its earnings, signalling a high quality of reported earnings and healthy accounting practices. In contrast, Company Y, with only a 20% ratio, shows a significant discrepancy between cash flow and earnings, which may be a sign of aggressive accounting or earnings manipulation. This makes Company X a more reliable choice from a forensic viewpoint.



NIFTY 500 TRI Vs Low Operating Cash Flow to EBITDA



From Sep 2006 to Dec 2024	CAGR (%)	10 Year Median Rolling Returns (%	Annualised Volatility (%)	3-Year Minimum Rolling Return (%)	3-Year Probability of Loss (%)
Low OCF to EBITDA 100	5.88	3.30	25.56	-24.14	35.27
Nifty 500 TRI	12.92	13.03	20.18	-6.31	4.22

Worst 5 Drawdowns	Drawdown of Low OCF to EBITDA Portfolio	Drawdown of Nifty 500	Drawdown Date	Recovery Time (Days) for Low OCF to EBITDA Portfolio	Recovery Time (Days) for Nifty 500
1	-76.55%	-63.71%	27-10-2008	5,709	1,977
2	-46.24%	-38.11%	23-03-2020	255	228
3	-34.72%	-20.06%	25-02-2016	410	148
4	-18.66%	-17.77%	20-06-2022	74	148
5	-22.75%	-15.64%	26-10-2018	853	398

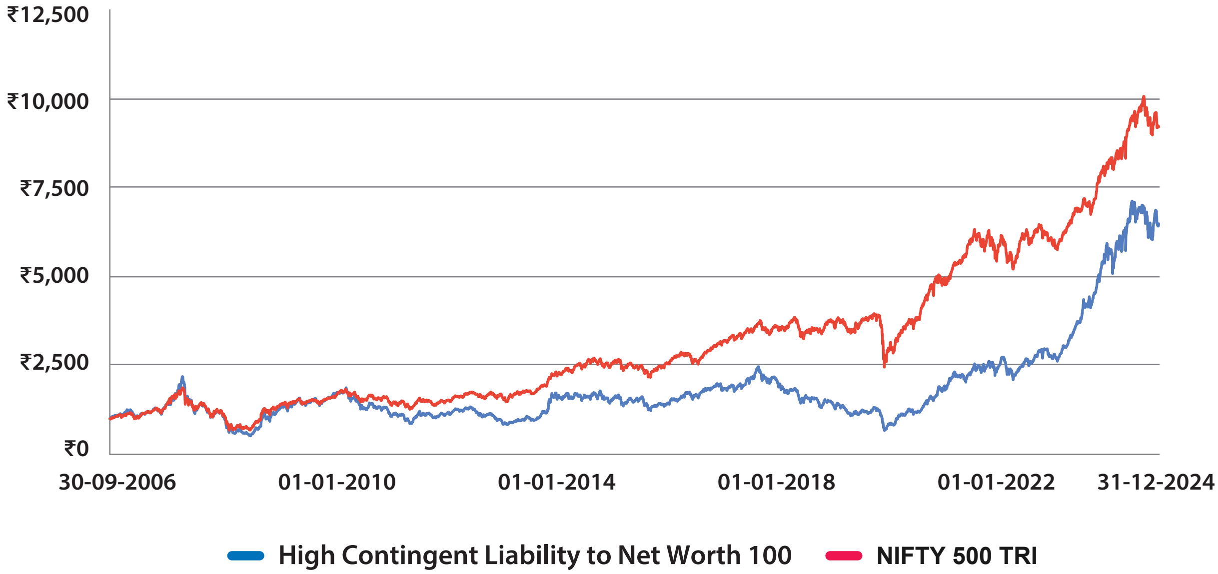
Source: CMIE, NJ's Smart Beta Platform. Data from September 30, 2006, to December 31, 2024. The Low OCF to EBITDA Portfolio consists of companies falling in the bottom decile based on their OCF to EBITDA values. Only Non Financial companies are considered. Companies with negative EBITDA are not considered. Probability of Loss (%) is calculated by dividing the number of negative observations by total number of observations. Past performance may or may not be sustained in the future and is not an indication of future returns.

3) Contingent Liabilities to Net Worth: This parameter assesses potential obligations, often camouflaged in the notes outside a company's balance sheet, that could impact a company's financial stability and solvency. A high ratio indicates that contingent liabilities if recognised as actual and measurable liabilities, pose significant risks to a company's future net worth.

Company	Contingent Liabilities to Net Worth (%)
M	5%
N	25%

Company M, with a 5% contingent liabilities to net worth ratio, is in a stronger financial position, as its contingent liabilities are relatively low compared to its net worth. In contrast, Company N, with a 25% ratio, faces higher financial uncertainty, as its contingent liabilities could potentially affect its financial stability and earnings in the future. Even in the worst-case scenario, if all of Company M's and Company N's contingent liabilities are later recognised as liabilities, then Company M's net worth would decrease by just 5% whereas Company N's resultant net worth would be equal to only 75% of its original net worth. This makes Company M a more safe investment when considering potential balance sheet risk.

NIFTY 500 TRI Vs High Contingent Liability to Net Worth



From Sep 2006 to Dec 2024	CAGR (%)	10 Year Median Rolling Returns (%	Annualised Volatility (%)	3-Year Minimum Rolling Return (%)	3-Year Probability of Loss (%)
High Contingent Liability to Net Worth 100	10.79	5.69	24.45	-29.21	29.24
Nifty 500 TRI	12.92	13.03	20.18	-6.31	4.22

Worst 5 Drawdowns	Drawdown of High Contingent Liability to Net Worth Portfolio	Drawdown of Nifty 500	Drawdown Date	Recovery Time (Days) for High Contingent Liability to Net Worth Portfolio	Recovery Time (Days) for Nifty 500
1	-72.03%	-63.71%	27-10-2008	3,329	1,977
2	-48.29%	-38.11%	23-03-2020	242	228
3	-28.70%	-20.06%	25-02-2016	239	148
4	-17.77%	-17.77%	20-06-2022	67	148
5	-21.66%	-15.64%	26-10-2018	858	398

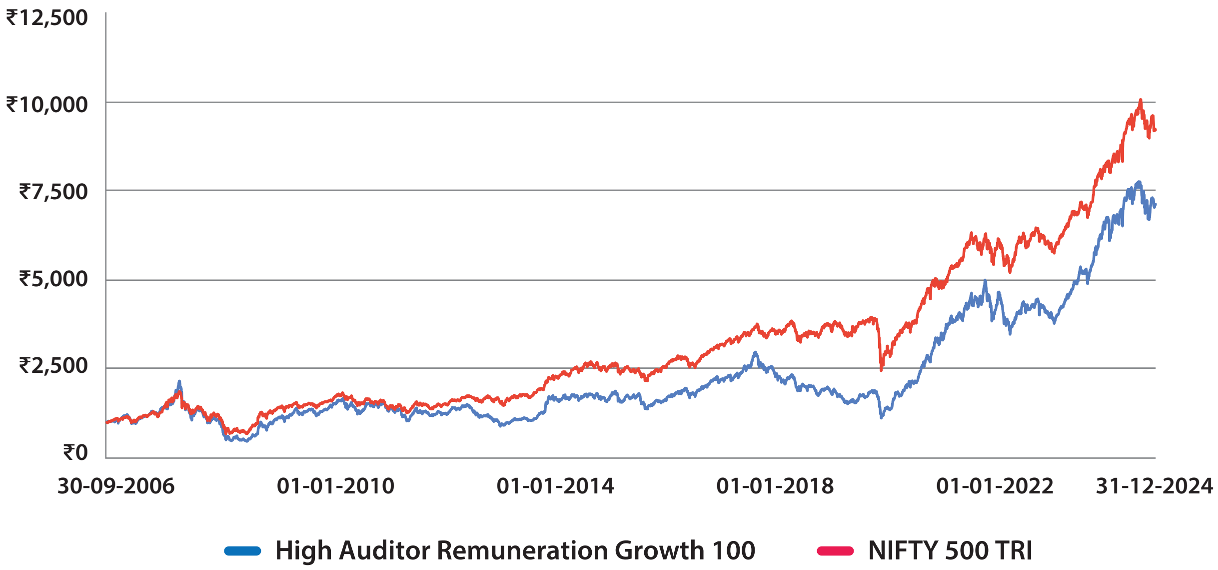
Source: CMIE, NJ's Smart Beta Platform. Data is from September 30, 2006 to December 31, 2024. The High Contingent Liability to Net Worth Portfolio consists of companies in the top decile with the highest Contingent Liability to Net Worth parameter values in the Nifty 500 universe. Companies with negative Net Worth and Lending companies are not considered. Probability of Loss (%) is calculated by dividing the number of negative observations by total number of observations. Past performance may or may not be sustained in the future and is not an indication of future returns.

4) Auditor Remuneration Growth: A significant increase in auditor fees may indicate potential conflicts of interest, a lack of independence, or the need for more extensive auditing due to concerns about the company's financial health. If auditor fees rise disproportionately compared to revenue or profit growth, it could suggest undisclosed financial risks, increased scrutiny, or potential financial misreporting.

Company S	
Revenue	15%
Auditor Fees	70%

For example, Company S reported a 15% increase in revenue but a 70% surge in auditor fees, raising questions about possible financial irregularities requiring deeper scrutiny. Instead of looking at absolute changes, comparing the auditor remuneration growth relative to sales or earnings growth provides a better indication of compromise in the auditor's independence.

NIFTY 500 TRI Vs High Auditor Remuneration Growth



From Sep 2006 to Dec 2024	CAGR (%)	10 Year Median Rolling Returns (%	Annualised Volatility (%)	3-Year Minimum Rolling Return (%)	3-Year Probability of Loss (%)
High Auditor Remuneration Growth 100	11.35	10.01	22.70	-18.78	19.85
Nifty 500 TRI	12.92	13.03	20.18	-6.31	4.22

Worst 5 Drawdowns	Drawdown of High Auditor Remuneration Growth Portfolio	Drawdown of Nifty 500	Drawdown Date	Recovery Time (Days) for High Auditor Remuneration Growth Portfolio	Recovery Time (Days) for Nifty 500
1	-76.61%	-63.71%	27-10-2008	3,082	1,977
2	-39.52%	-38.11%	23-03-2020	105	228
3	-23.90%	-20.06%	25-02-2016	176	148
4	-25.12%	-17.77%	20-06-2022	381	148
5	-19.22%	-15.64%	26-10-2018	756	398

Source: CMIE, NJ's Smart Beta Platform. Data is from September 30, 2006 to December 31, 2024. The High Auditor Remuneration Growth Portfolio consists of the companies from the Nifty 500 universe with the highest growth in auditors' remuneration parameter values. Probability of Loss (%) is calculated by dividing the number of negative observations by total number of observations. Past performance may or may not be sustained in the future and is not an indication of future returns.

Other Parameters

- **Capital Work in Progress (CWIP) to Net Fixed Assets (NFA):** A high CWIP to NFA ratio may indicate stalled projects or inefficient asset utilization, which can be a red flag for investors. While a moderate level of CWIP is expected in growing companies, a consistently high CWIP over multiple years could signal governance lapses, where assets are kept under development to defer depreciation and inflate profits. A temporary spike in CWIP may be justified in the early stages of expansion, but if the ratio remains elevated over an extended period, it raises concerns about cost overruns, mismanagement, or financial manipulation.

For example, Company P, with a five-year median CWIP to NFA of 10%, reflects efficient capital deployment and a well-managed expansion strategy. In contrast, Company Q, with a consistently high five-year median ratio of 50%, suggests prolonged asset construction, increasing the risk of inefficiencies and potential governance concerns.

- **Goodwill & Impairment:** Sudden impairments in goodwill can indicate that previous acquisitions were overvalued or that the company is struggling with post-acquisition integration. While one-time impairments may be due to changing business conditions, frequent or substantial goodwill write-offs relative to the total intangible assets can reflect deeper issues, such as flawed valuation methods, poor acquisition strategies, aggressive accounting practices, or financial mismanagement.

For instance, Company R had goodwill making up a significant portion of its total intangible assets, but within two years of acquiring a subsidiary, it impaired goodwill equivalent to 40% of its total intangible assets. Such a high goodwill impairment ratio relative to intangible assets raises concerns about management's due diligence in M&A decisions and the potential misrepresentation of financial health and a bloated balance sheet in prior years.

- **Inconsistent Tax Recognition:** A company's tax management approach reflects its financial transparency and governance. Significant fluctuations in the effective tax rate may signal aggressive strategies to manipulate profits. While some variability is normal owing to deferred taxes arising due to differences in accounting treatment as per the financial reporting standards and the Income Tax laws, erratic swings can raise concerns about integrity. Additionally, the ratio of cumulative tax expense reported in the P&L to the actual tax payments reported in the cash flow statement over a medium to long period offers insight into tax consistency. A persistent mismatch between reported and actual tax payments may indicate earnings management. Companies with stable tax rates and alignment between reported and actual paid taxes often demonstrate stronger governance, while extreme volatility warrants closer scrutiny.

For example, Company R has maintained a stable effective tax rate of around 25% over the past five years, with only slight variations due to regulatory changes. The ratio of its cumulative P&L taxes to cumulative cash flow taxes is consistent. In contrast, Company S has experienced significant fluctuations in its effective tax rate, ranging from 15% to 35% over the past five years. Additionally, its cumulative P&L taxes significantly underestimate its actual tax payments, raising concerns about aggressive accounting practices such as underestimation of taxes to artificially boost profits. This inconsistency suggests potential earnings management, warranting further scrutiny of the company's financial integrity.

- **Volatility in Depreciation Rate:** Significant fluctuations in depreciation rates can distort the earnings quality of a company. Frequent changes in depreciation methods, estimates or rates without significant changes in a company's property, plant, and equipment (PP&E) may be a sign of earnings management, where companies adjust depreciation to influence profits.

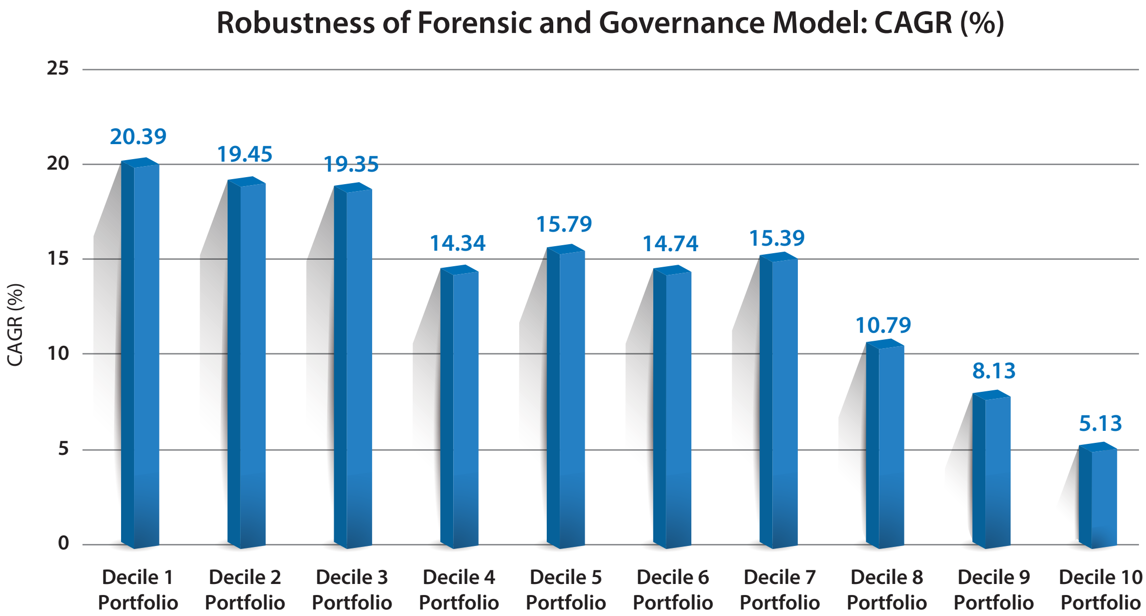
A stable and consistent depreciation rate and policy are important for assessing a company's financial health and ensuring that its reported earnings are reflective of its true performance.

For example, Company T reduced its depreciation rate by 30% in a single year, artificially boosting profits, only to reverse the policy a year later, highlighting potential earnings manipulation.

7.6 Robustness of Forensic & Governance Model

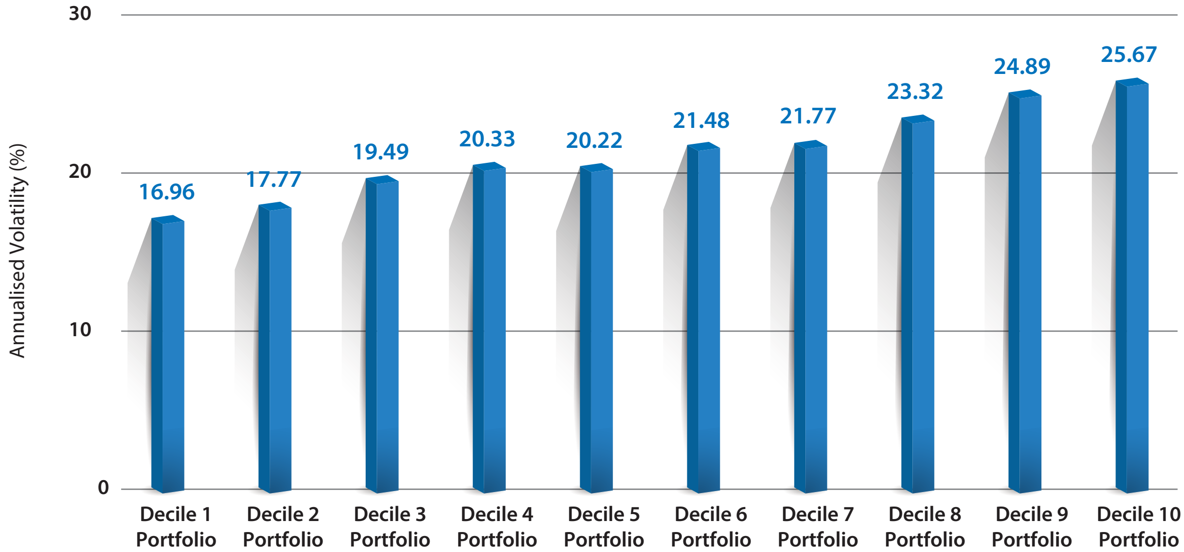
At NJ AMC, our Forensic & Governance Model is built to systematically detect forensic and governance laggards through a quantitative scoring framework. By evaluating key forensic parameters, the model identifies companies with potential financial weaknesses or governance risks. This structured approach helps filter out firms with red flags, ensuring a more robust portfolio while enhancing factor strategies and long-term risk-adjusted returns.

Based on the Forensic and Governance model, a specific score is assigned to each company in the Nifty 500 index. The companies are then grouped into 10 deciles, with Decile 1 comprising the highest-scoring companies and Decile 10 the lowest. Our portfolio strategies tend to eliminate companies falling the last two deciles based on this proprietary Forensic & Governance Model to safeguard the portfolios from potential corporate shenanigans. This process is repeated for every rebalancing date, and cumulative results of performance parameters are analyzed, as illustrated in the following charts.



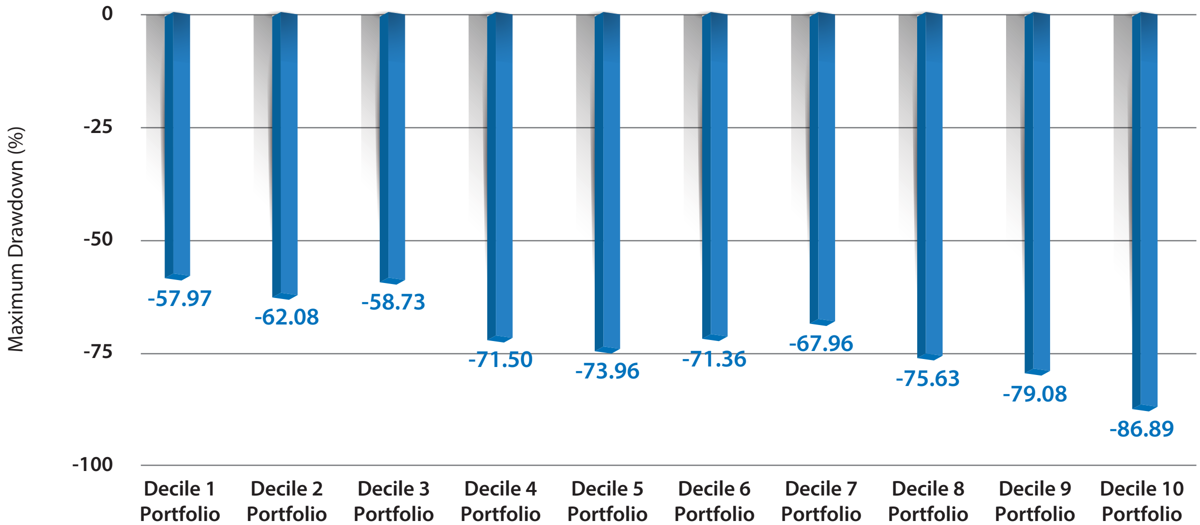
Source: CMIE, NJ's Smart Beta Platform. Data is from September 30, 2006 to December 31, 2024. The portfolios are constructed by ranking all Nifty 500 companies based on their forensic model scores and dividing them into ten deciles. Each decile forms a separate portfolio, with Decile 1 containing the highest-scoring companies and Decile 10 the lowest. Past performance may or may not be sustained in the future and is not an indication of future returns.

Robustness of Forensic and Governance Model: Annualised Volatility (%)



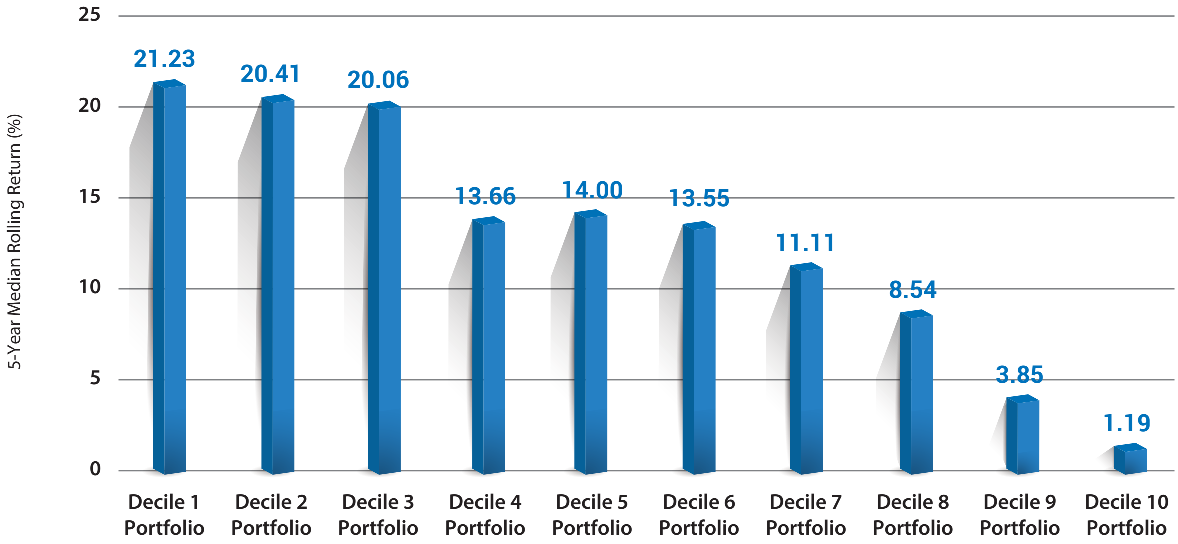
Source: CMIE, NJ's Smart Beta Platform. Data is from September 30, 2006 to December 31, 2024. The portfolios are constructed by ranking all Nifty 500 companies based on their forensic scorecard scores and dividing them into ten deciles. Each decile forms a separate portfolio, with Decile 1 containing the highest-scoring companies and Decile 10 the lowest. Past performance may or may not be sustained in the future and is not an indication of future returns.

Robustness of Forensic and Governance Model: Maximum Drawdown (%)



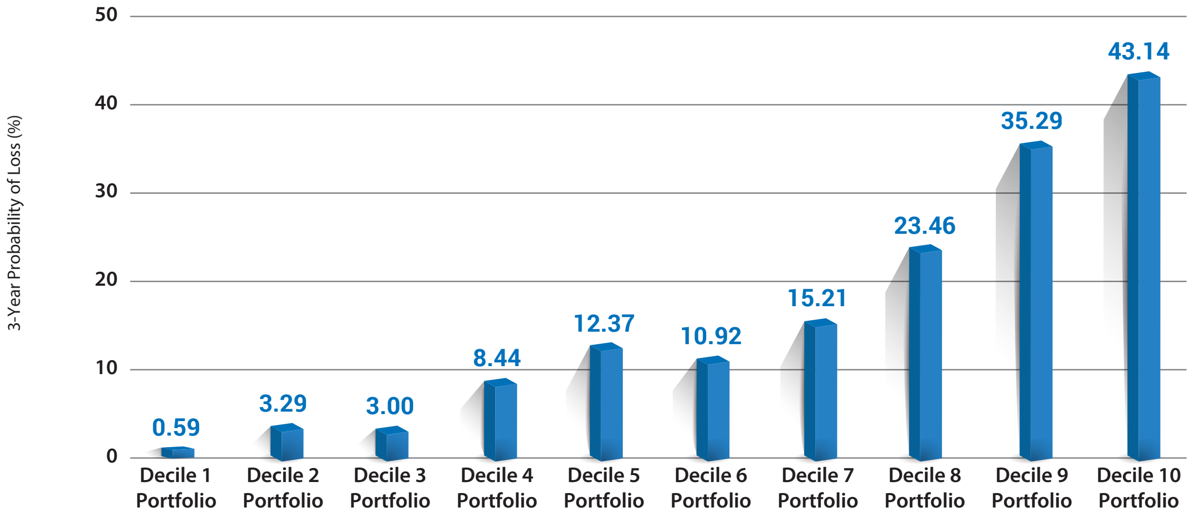
Source: CMIE, NJ's Smart Beta Platform. Data is from September 30, 2006 to December 31, 2024. The portfolios are constructed by ranking all Nifty 500 companies based on their forensic scorecard scores and dividing them into ten deciles. Each decile forms a separate portfolio, with Decile 1 containing the highest-scoring companies and Decile 10 the lowest. Past performance may or may not be sustained in the future and is not an indication of future returns.

Robustness of Forensic and Governance Model: 5-Year Median Rolling Return (%)



Source: CMIE, NJ's Smart Beta Platform. Data is from September 30, 2006 to December 31, 2024. The portfolios are constructed by ranking all Nifty 500 companies based on their forensic scorecard scores and dividing them into ten deciles. Each decile forms a separate portfolio, with Decile 1 containing the highest-scoring companies and Decile 10 the lowest. Past performance may or may not be sustained in the future and is not an indication of future returns.

Robustness of Forensic and Governance Model: 3-Year Probability of Loss



Source: CMIE, NJ's Smart Beta Platform. Data is from September 30, 2006 to December 31, 2024. The portfolios are constructed by ranking all Nifty 500 companies based on their forensic scorecard scores and dividing them into ten deciles. Each decile forms a separate portfolio, with Decile 1 containing the highest-scoring companies and Decile 10 the lowest. Past performance may or may not be sustained in the future and is not an indication of future returns.

The charts above clearly demonstrate a strong correlation between accounting quality and investment performance and risk. Portfolios with higher forensic and governance scores (Deciles 1–3) consistently outperform, delivering higher CAGR with lower volatility and reduced drawdowns. These results highlight the effectiveness of forensic screening in identifying financially sound companies with stronger governance.

Conversely, lower forensic and governance score portfolios (Deciles 8–10) suffer from diminishing returns (CAGR) alongside heightened volatility and severe drawdowns. Their high 3-year probability of loss further reinforces the risk of investing in companies with governance and financial red flags.

Scams are rarely sudden events. They are typically the result of years of financial misrepresentation and governance lapses. This reinforces the importance of forensic and governance analysis as a critical tool for early detection. By identifying potential red flags at an early stage, such analysis acts as a safeguard against significant financial and reputational damage.

Proactive measures like these not only help in mitigating risks but also contribute to building a more resilient, transparent and robust investment ecosystem.

Upon further analysis, the table below highlights key companies that exhibited persistent governance issues and financial weaknesses, placing them in the bottom two deciles for years before their respective scams were exposed.

Company Name	Year Scam Unfolded	Years in Bottom 2 Deciles	Potential Saving	Key Red Flags as per Model
IL & FS Transportation Networks Ltd.	**2018**	**2014 - 2018**	**95.40%**	**Consistently high Capital Work-In-Progress (CWIP), High and sustained promoter pledge**
Manpasand Beverages Ltd.	**2019**	**2016 - 2018**	**96.29%***	**Inconsistent Tax Recognition, Sharp increase in auditor fees over consecutive years**
Jet Airways (India) Ltd.	**2019**	**2016 - 2018**	**91.06%**	**High Contingent Liabilities relative to Net Worth, Significant goodwill impairment**
Cox & Kings Ltd.	**2020**	**2011 - 2019**	**46.43%**	**Significant goodwill impairment, High and sustained promoter pledge**
Religare Enterprises Ltd.	**2018**	**2009 - 2017**	**60.97%**	**Inconsistent Tax Recognition, High and sustained promoter pledge**

Source: CMIE, NJ's Smart Beta Platform. The portfolios are constructed by ranking all Nifty 500 companies based on their forensic scorecard scores and dividing them into ten deciles. Each decile forms a separate portfolio, with Decile 1 containing the highest-scoring companies and Decile 10 the lowest. Potential saving is calculated as maximum drawdown within 1 year from the date on which the scam unfolded. Prices are adjusted for corporate actions. Past performance may or may not be sustained in the future and is not an indication of future returns. The above should not be construed as a recommendation to buy/sell any stocks specified above. The above content is based on the internal research process. The AMC may or may not hold the above stock in its portfolio. Investors should consult their own advisors, and tax consultants before making any decision. * For Manpasand Beverages Ltd. max drawdown is considered from the date of unfolding of the scam till the date the stock was listed.

For instance, Manpasand Beverages, a fast-growing FMCG company, saw meteoric stock price gains before its auditors resigned in 2019, citing financial irregularities. However, our model had flagged the company well before this event, consistently placing it in the bottom deciles. As the fraud came to light, the stock plummeted, eventually losing nearly 48% value in just 4 days.

Similarly, the IL&FS crisis in 2018, exposed massive debt defaults and poor governance, causing a major shock to India's financial markets. However, our forensic and governance model had flagged the company much earlier, consistently placing it in the bottom deciles due to its weak financials and governance concerns.

The case of Cox & Kings Ltd. further illustrates how financial frauds often build up over time. The company, which defaulted on debts worth ₹5,500 crore in 2020, was involved in fund diversion, fake transactions, and inflated revenues. Yet, our forensic model had detected these governance issues as early as 2011, consistently placing it in the bottom two deciles for years. A similar pattern emerged with Religare Enterprises Ltd., where the company orchestrated a ₹2,397 crore fraud by diverting funds. Our model had flagged governance concerns as early as 2009, long before the fraud was uncovered in 2018.

Lastly, Jet Airways' collapse was a cautionary tale of how financial mismanagement, excessive debt and governance failures can lead to failure. The accumulation of excessive debt of around 8,500 crores while mismanaging cash flows was a clear indication of red flags leading to its placement in the bottom 2 deciles for several years.

7.7 Forensic and Governance Analysis: The Safety Net of Investments

Forensic and governance analysis is not about predicting fraud, it's about creating a safety net for investors. A robust governance framework ensures that companies operate with integrity, protecting shareholders from financial disasters.

By incorporating forensic checks into factor investing, NJ AMC ensures that investment strategies are built on reliable, high-quality data. In the financial landscape, governance isn't just a corporate responsibility, it's the first line of defence against value destruction.

8. Investment **Process**

"The essence of investment management is the management of risks, not the management of returns."
– Benjamin Graham

"Without data, you're just another person with an opinion."
– W. Edwards Deming

For More Details

8. Investment **Process**

Investing public money is a responsibility that demands transparency, discipline, and a well-defined process. A sound investment process ensures that every decision is backed by data, research, and tested methodologies rather than emotions or market noise.

At NJ Asset Management Company (NJ AMC), we uphold these principles through a comprehensive, systematic rule-based investment research process that helps avoid human bias and navigate financial markets effectively. Let's dive into the best practices that make our investment process robust and help us increase the efficacy of our rule-based portfolios.

8.1 Data Validation, Verification & Cleansing

We treat data as a precious asset, ensuring its accuracy is non-negotiable. To begin with, our Investment Research Analysts collaborate closely with the Data & Analytics Team to validate, verify, and cleanse the data. This step eliminates errors, inconsistencies, and anomalies, ensuring that only clean, comparable, and reliable data guides our decision-making process.

For us, the sanctity of the raw data is as important as the sanctity of defined rules when implementing rule-based investing strategies.

8.2 Development of Factor Parameters & Hygiene Check

With clean data in hand, we now zoom in on the core building blocks—factor parameters.

Factor investing is like a puzzle—without the right parameters, the picture remains incomplete. Various parameters, such as Return on Capital Employed (ROCE), Return on Equity (ROE), and Free Cash Flow (FCF), among others, act as lenses through which we evaluate potential factors. Each parameter undergoes a rigorous development process, using customised parameter definitions, followed by a hygiene check to guarantee accuracy.

Customising parameter definitions and conditions, instead of using readily available parameter values, is essential for effective factor investing since even small adjustments to parameter definitions can have a significant impact on the backtesting results. For instance, a simple parameter like Return on Equity (ROE) can be computed using various definitions and adjustments for net income.

Once verified, the parameter is added to our Parameter Library, ready to be integrated for future analyses.

8.3 Parameter Robustness Testing

It's time to separate signal from noise—by subjecting our parameters to rigorous stress tests, we identify the most robust and reliable ones. This step filters out the weak, ensuring only the strongest parameters make the cut. Through comprehensive backtesting across various conditions, we gain valuable insights into their real-world performance.

The structured robustness is carried out by ranking a stock universe based on the chosen parameter, dividing it into different equally sized slices (e.g., terciles, quartiles, quintiles), and analyzing the performance of these slices over various timeframes. Ensuring that an equal number of stocks are distributed across slices is imperative.

The rationale behind this approach is simple: if a parameter effectively contributes to performance, the highest-ranked group should generate better returns than the group below it, which in turn should outperform the next one, and so forth. Additionally, volatility should increase as one moves towards the lower-ranked slices.

For example, take a universe of the 150 largest companies by market capitalization. If these stocks are categorized into three equal groups of 50 each based on a specific parameter (let's call it ABC), the top slice (highest 50 stocks) would contain the best-ranked stocks, while the lowest slice (bottom 50 stocks) would include the least favourable ones, based on the required characteristics for the parameter ABC.

Portfolio Slices	15 Years Annualised Return	5 Years Rolling Mean Return	15 Years Annualised Volatility	Maximum Drawdown
Parameter ABC 1st Slice (Stocks Ranked 1 to 50)	**17.24%**	**13.64%**	**12.05%**	**-43.68%**
Parameter ABC 2nd Slice (Stocks Ranked 51 to 100)	**12.46%**	**8.48%**	**14.96%**	**-50.45%**
Parameter ABC 3rd Slice (Stocks Ranked 101 to 150)	**9.78%**	**6.92%**	**17.01%**	**-65.29%**

Parameter name replaced with ABC for illustrative purposes. Past performance may or may not sustain in future.

This example highlights the robustness of parameter ABC, as stocks with higher rankings based on this parameter exhibit a stronger risk-return profile compared to those ranked lower. In other words, the effectiveness of parameter ABC in stock selection is well justified, as incorporating higher-ranked stocks, based on the parameter ABC, into a portfolio can potentially lead to superior returns, reduced volatility, and minimized drawdowns.

Robustness testing plays a crucial role in identifying strong parameters that contribute positively to investment decisions. By systematically filtering out weaker indicators, investors can focus on parameters that enhance portfolio returns while managing risk effectively.

8.4 Idea Generation & Portfolio Construction

With battle-tested parameters in place, we move to the next frontier—turning insights into unique portfolio strategies. Our research team customises these strategies by defining the universe of stocks, portfolio size, selection criteria, weighting methodology, and the rebalancing frequency and period. This flexibility ensures that portfolios align with the investment objectives.

- **Universe Selection and Portfolio Size:** The first step in the investment process is selecting an appropriate universe, which generally consists of all the constituents of a broad-based index viz. Nifty 500. Along with defining a suitable universe, determining the right portfolio size is equally crucial. The portfolio should include an optimal number of stocks to strike a balance, ensuring it is neither too concentrated nor overly diversified, while aligning with the scheme's objectives.

- **Stock Selection:** Next, we define the factors that will guide the portfolio generation, along with specific parameters within these factors. Finally, the weight assigned to each parameter and factor within the portfolio is determined.
- **Portfolio Allocation:** At this stage, we decide how to allocate weights to the individual stocks within the portfolio. This could involve various methodologies, such as equal weighting, market capitalization weighting, factor weighting, and inverse market capitalization weighting among others.
- **Portfolio Rebalancing:** Rebalancing frequency is established, whether on a monthly, quarterly, half-yearly, or yearly basis.

Once all these elements are defined, the final portfolio is constructed. Thousands of such portfolio strategies are backtested by the Research Team using the proprietary NJ Smart Beta Research Platform.

8.5 Analysis of The Portfolio Strategy

A portfolio without analysis is like a ship without a compass. It is critical to dissect a portfolio's performance to ensure it stays on course. We leverage the NJ Smart Beta Research Platform to do so. This process encompasses multiple key aspects:

A. Performance Analysis: We assess various performance metrics to gauge the portfolio's effectiveness in long duration as well as in different cycles. A few of these metrics include:

- **Point-to-Point Returns:** Long-term point-to-point CAGR generated over time.
- **Sharpe Ratio & Sortino Ratio:** Risk-adjusted return measures.
- **Rolling Returns:** Performance consistency over different holding periods viz. 1 year, 3, years, 5 years and 10 years.
- **Maximum Drawdown:** Maximum decline from peak to trough in different market cycles.
- **Calendar Year Returns:** Annualized returns for individual calendar years.
- **Volatility:** Degree of fluctuations in returns.

This comprehensive analysis sheds light on how our model portfolios stack up against industry standards and benchmark indices such as Nifty 500 TRI, and Nifty 50 TRI.

The table below compares two quality-factor strategies created by a researcher using the NJ Smart Beta Platform:

	Cumulative Returns (%)	Sharpe Ratio	Sortino Ratio	10 Year Median Rolling Returns	Max Drawdown (%)	Volatility (%)
Portfolio A	19.50	0.60	0.90	19.76	-59.05	16.86
Portfolio B	13.66	0.35	0.53	10.54	-63.00	20.76
Nifty 500 TRI	12.65	0.32	0.46	13.04	-63.71	20.18
Nifty 500 Quality 50 TRI	16.80	0.53	0.80	16.21	-53.60	17.40

Source: Internal research, CMIE, NSE. The period for calculation is 30th September 2006 to 31st December 2024. Past performance may or may not be sustained in future and is not an indication of future return.

Portfolio A outperforms both Nifty 500 TRI and Nifty 500 Quality 50 TRI, delivering higher returns, better risk-adjusted efficiency, and greater resilience during market downturns against Nifty 500 TRI. Portfolio B, while slightly better than Nifty 500 TRI in terms of returns and downside risk, significantly underperforms Nifty 500 Quality 50 TRI across all the key metrics. This makes Portfolio A a better choice, while Portfolio B struggles against quality-focused investing.

Note that it is imperative to benchmark the factor based strategies not just against broad market indices but also against relevant passive factor based strategy indices such as Nifty 500 Quality 50 TRI as demonstrated above.

B. Attribution Report: The portfolio attribution analysis includes key performance parameters such as:

- **Average Weight (%):** This represents the average proportion of the portfolio allocated to a particular stock or sector across the backtesting period.
- **Total Return in Portfolio (%):** This indicates the overall return percentage generated by a particular stock or sector within the portfolio.
- **Total Return Contribution (%):** This measures how much of the portfolio's total return is contributed by a particular stock or sector. Even if a stock or a sector has a high return, its contribution may be low if its weight in the portfolio is small.
- **Gain-To-Loss Ratio:** This measures the ratio of the count of instances where a stock or a sector has generated a positive return in the portfolio from its inclusion date to the subsequent exit date to the count of instances where that same stock or sector has generated a negative return in the portfolio from its inclusion date to the subsequent exit date.

C. Churn Analysis: This is a crucial aspect of portfolio evaluation, as it helps assess the frequency and magnitude of transactions within a portfolio. A high churn rate often indicates frequent and heavy buying and selling of securities, which can lead to significant transaction costs, impacting net returns.

Why is Churn Analysis Important?

- **Transaction Costs:** Higher churn means more trades, leading to higher brokerage fees, taxes, and other costs that reduce overall returns.
- **Portfolio Stability:** Frequent trades may indicate a lack of consistency in strategy, potentially increasing risk.
- **Return Optimization:** The goal is to maximize returns while keeping transaction costs minimal to enhance net profitability.

Let us consider an example as follows,

Portfolio	Back-tested Return	Churn	Net Impact
A	20%	90%	High transaction cost reduces net return
B	19%	30%	Lower transaction cost preserves more of the return

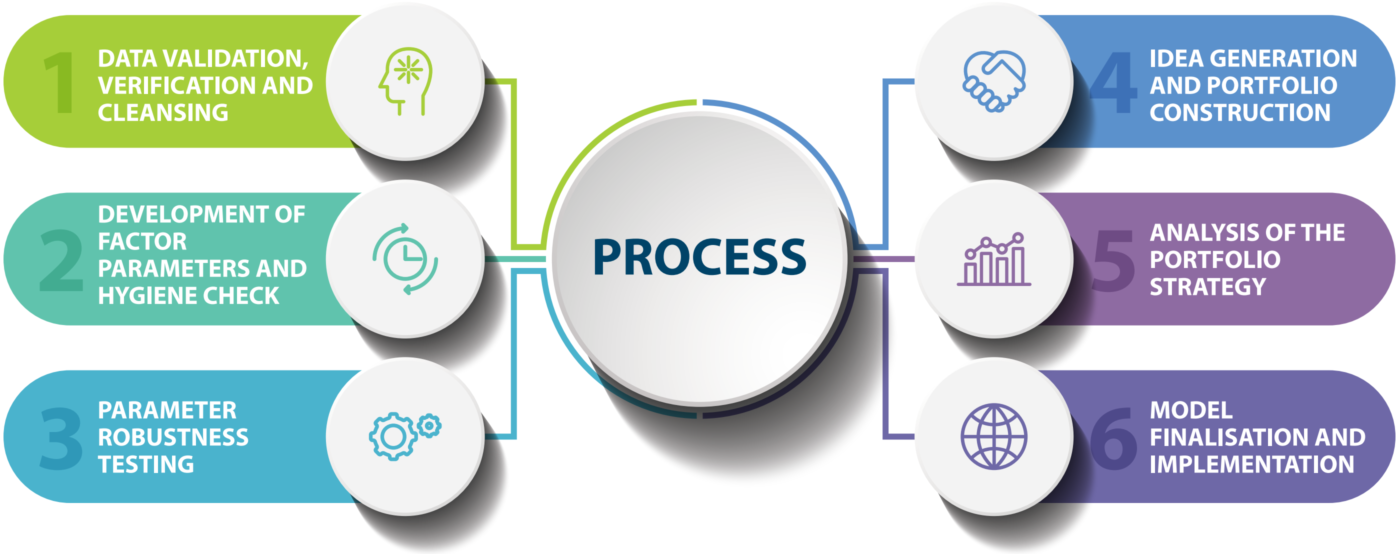
Even though Portfolio A offers a slightly higher return (20% vs. 19%), its high churn (90%) leads to increased transaction costs. In contrast, Portfolio B, with lower churn (30%), retains more of its return. As a result, the net returns of both portfolios may end up being similar, making Portfolio B a more efficient choice.

Thus, lower churn is generally better as it helps optimize returns by minimizing unnecessary costs.

8.6 Model Finalisation & Implementation

The final stretch—our strategy has been refined, tested, and optimized. Now, it's time to bring it to life. Here our investment committee reviews and evaluates the research output. Only strategies that pass rigorous audit checks and demonstrate a strong potential for risk-adjusted returns are approved for implementation. These strategies are then seamlessly integrated into both new and existing portfolios.

The investment committee does a thorough liquidity analysis of the strategy before implementation to ensure efficient deployment of funds as per the strategy with minimal impact costs and slippages.

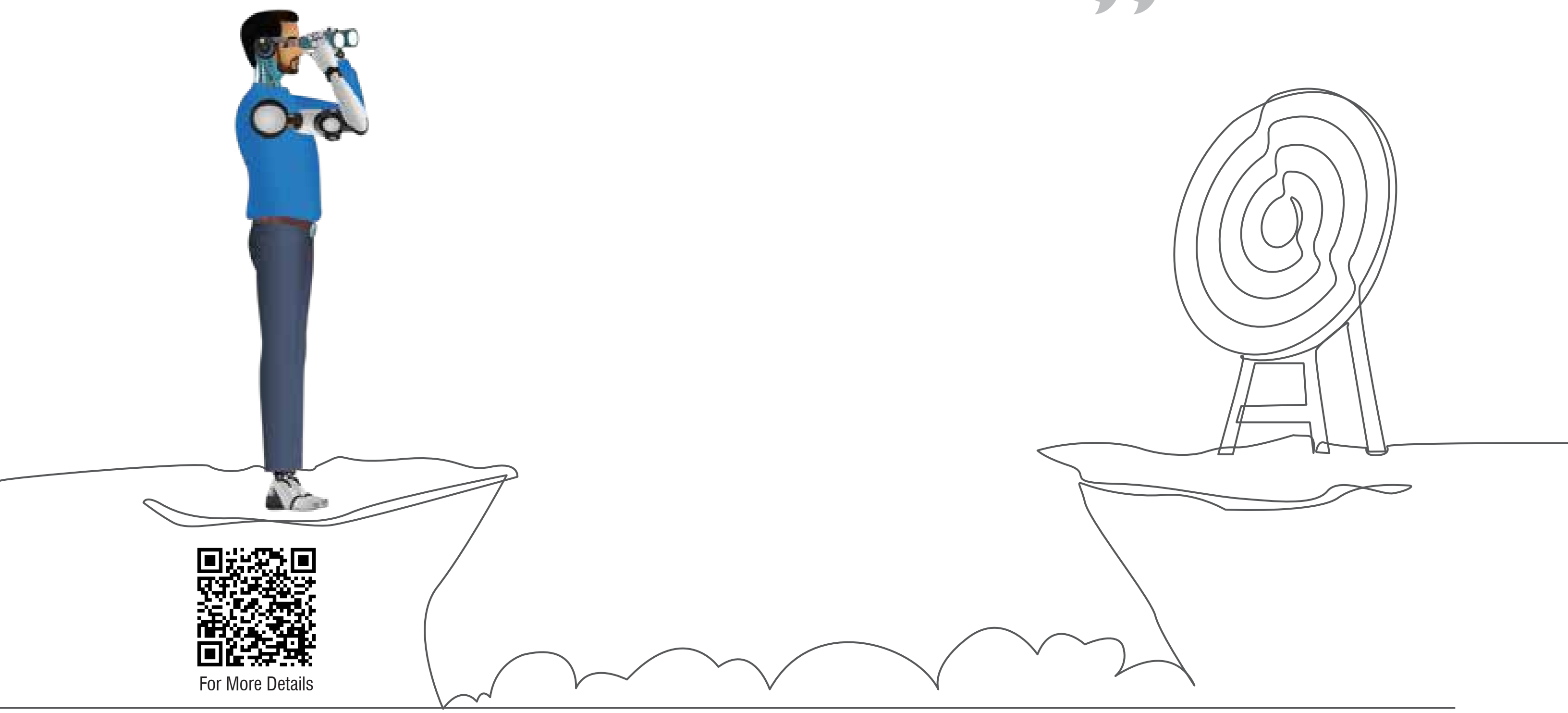


At NJ AMC, we've taken the guesswork out of investing. By minimizing human biases and adhering to a rule-based approach, we create portfolios that are aligned with predefined objectives. This reduces the need for constant human intervention, ensuring a consistent, reliable investment experience

9. Factor Investing: **The Road Ahead**

How many millionaires do you know who have become wealthy by investing in savings accounts? I rest my case.
-Robert G. Allen

The biggest risk of all is not taking one.
-Mellody Hobson



For More Details

9. Factor Investing: **The Road Ahead**

Factor investing has witnessed remarkable growth over the past decade, redefining how investors approach equity markets. With a growing emphasis on systematic, rule-based strategies, Smart Beta ETFs have become a preferred vehicle for factor-based investing. The surge in Assets Under Management (AUM) across various factor categories highlights the increasing adoption and confidence in these strategies.

The following table showcases the factor-wise AUM growth of equity Smart Beta ETFs in the USA over the last decade, reflecting how investor preferences have evolved:

FACTOR-WISE GROWTH OF EQUITY SMART BETA AUM OVER THE LAST DECADE

Factor	AUM as of 31st December 2014 ($ Million)	AUM as of 31st December 2024 ($ Million)	AUM Growth
Quality	4,671.92	100,193.80	35.87%
Value	94,553.50	482,121.16	17.69%
Momentum	3,533.41	27,454.01	22.76%
Low Volatility	14,411.58	50,788.47	13.42%
Size	26,762.84	149,838.74	18.80%
Growth	98,460.16	642,604.01	20.63%
Multi-factor	33,929.15	206,846.91	19.81%
Others	121,455.04	542,383.68	16.14%
Total	397,777.61	2,202,230.77	18.66%

Source: Bloomberg Intelligence. The AUM Growth is measured as the Compounded Annual Growth Rate (CAGR) of factor-wise AUM from 31st December 2014 to 31st December 2024.

Alongside the rise in AUM, the number of factor-based ETFs has also grown significantly, demonstrating broader investor acceptance and increasing product availability. The table below provides insights into the expansion of factor-based ETFs over the past decade. The expansion in the number of ETFs highlights how factor-based strategies have transitioned from niche offerings to mainstream investment solutions.

Factor	No. of factor-based ETFs in 2014	No. of factor-based ETFs in 2024
Quality	8	28
Value	43	71
Momentum	18	29
Low Volatility	18	26
Size	44	48
Growth	39	53
Multi-factor	85	172
Others	94	343
Total	**349**	**770**

Source: Bloomberg Intelligence. Data as on 31st December 2024

Factor investing has been on a steady rise across the global investment landscape, and its future looks particularly promising in India. As this investment approach gains traction in the Indian market, NJ Asset Management Company has been stepping up to meet the challenge with innovative solutions and a forward-looking perspective.

One of the key hurdles to factor investing in India has been the scarcity of accessible factor-based strategies. Investors have faced a relative lack of choices, making it challenging to incorporate these strategies into their portfolios. Additionally, the dearth of comprehensive, high-quality data — both in terms of historical records and coverage of a wide range of companies — has posed a significant constraint.

NJ Asset Management Company, recognizing the potential of factor investing, has made significant strides in addressing these challenges. Over the past few years, the company has diligently curated a high-quality dataset covering a substantial number of companies, spanning more than two decades. This extensive database now serves as the cornerstone of NJ's factor-based strategies across its products, offering a reliable and robust foundation to build our portfolios upon.

Furthermore, NJ Asset Management Company boasts in-house data analytics capabilities, allowing for a deeper and more insightful exploration of the data. This synergy between comprehensive data and data analytics empowers NJ AMC to craft and manage factor-based strategies that align with their client's investment goals and risk profiles.

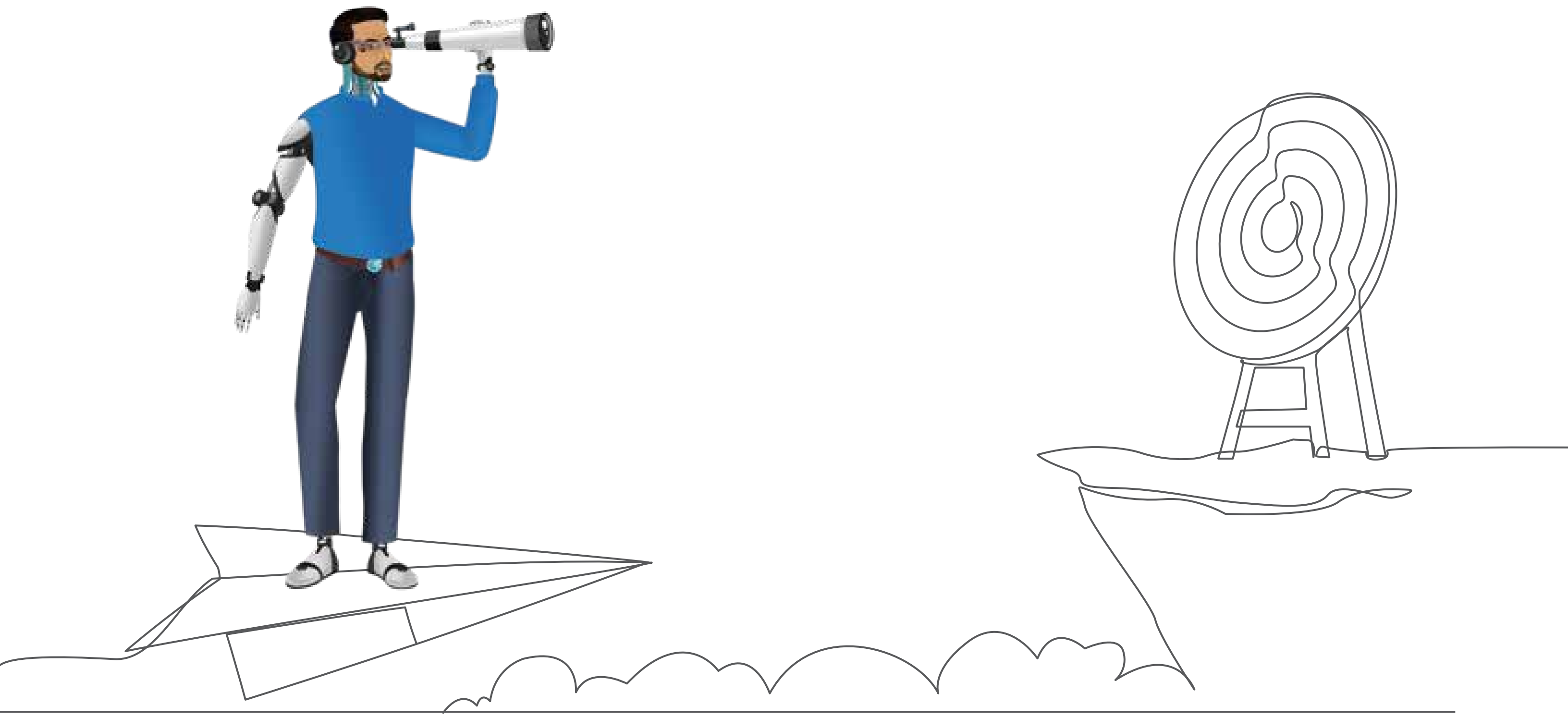
The future of factor investing in India is not only about expanding accessibility and data but also about innovation. NJ Asset Management Company is committed to pioneering rule-based strategies that adapt to the ever-evolving market dynamics. With computing power, data analytics, and evidence-based intelligence reshaping the investment landscape, NJ is at the forefront of this transformation.

One area where NJ AMC envisions significant progress is in the development of protocols that can assign weights to individual factors based on real-time market conditions. This dynamic approach promises to make factor investing even more efficient and effective. It's a crucial step towards fully adaptive protocols that leverage data-driven machine learning technologies. These adaptive protocols aim to offer investors a superior investment experience, unlocking the potential of factor-based investing for a broader audience.

The acceptance of factor-based strategies in India is poised to grow, with an increasing array of investment options and innovative strategies entering the market. NJ Asset Management Company, as the first exclusively dedicated rule-based asset manager in India, is determined to lead this endeavour. The adoption of factor-based strategies marks a shift in the investment landscape, providing an alternative to the traditional, discretionary approaches. This change is essential in eliminating human biases and ensuring time-bound rebalancing, offering investors a markedly different investment experience.

Furthermore, the mutual fund industry in India is at a nascent stage compared to the potential it holds. With the economy maturing and structural reductions in inflation rates, the preference for fixed-rate savings is expected to wane. This shift in financial behaviour is anticipated to drive the growth of professional asset management in the coming decades.

In conclusion, NJ Asset Management Company believes that factor-based strategies are set to become an integral part of the Indian investment landscape. These strategies, with their potential to generate positive excess returns in a cost-effective manner, coupled with ongoing research efforts to enhance the consistency of factor performance, will inevitably find their place in the portfolios of Indian investors, shaping the future of factor investing in the country. NJ Asset Management Company is poised to lead this change, ensuring that investors have access to innovative and adaptive strategies that can navigate the complexities of the evolving investment landscape.



10. **NJ Smart Beta**

A state of art factor research platform

SmartBeta Platform

A state of art factor research platform

Back-testing different factor-based quantitative portfolio strategies involves creating historical model portfolios across a long time horizon using the same quantitative rules and the available point-in-time historical data. Since this requires dealing with vast amounts of data and various permutations and combinations for rule-based selection and weighting of securities, it is heavily reliant on a robust technology platform and infrastructure. A strong technology platform, which is well integrated with a back-end database, can facilitate quick and seamless creation and analysis of a multitude of factor-based investment strategies. Such a platform can enable a factor-based asset manager to efficiently back-test a myriad rule-based portfolio strategies and quantitative ideas on a large universe of stocks over long periods by dynamically combining different rules pertinent to the use of factors and parameters for stock selection, portfolio weightages, and rebalancing frequencies among other inputs.

NJ Asset Management, a fully rule-based asset manager, has acknowledged the importance of a strong IT infrastructure for successfully employing factor-based investment methodologies. NJ Asset Management, in this endeavour, has developed the proprietary Smart Beta Platform, enabling its researchers to back-test factor-based strategies across a large universe of stocks, covering more than 1100 companies and 20 years of data. Through the Smart Beta Platform, research analysts can seamlessly analyse the historical performance of their back-tested portfolios vis-a-vis relevant benchmarks (for eg. Nifty 500 TRI, Nifty 50 TRI), historical composition of the portfolios including sectoral and market capitalisation exposures, portfolios' churn, and the portfolios' winners and laggards across different time periods

Watch the demo video of NJ AMC's Smart Beta Research Platform for details:

i) Smart Beta English:

https://www.youtube.com/watch?v=0LbhLAXY3AM (plus QR)

ii) Smart Beta Hindi:

https://www.youtube.com/watch?v=bbhaOmzNn4Y (plus QR)

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Contributors

NIRMAY CHOKSI
Director and Head of Investments

RAJ MEHTA
Lead Research Analyst

BHAVIK SHAH
Senior Research Analyst

DIVYAJEET DHADHAL
Senior Research Analyst

AASHVI SHAH
Research Content Creator

PRIYANSHI SINGHI
Research Content Creator

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