Journal of Informatics Education and Research
ISSN: 1526-4726
Vol 4 Issue 3 (2024)

ESG and Smart Beta Investing: A Synergistic Approach to Indian Equity Investing using the NIFTY 100 ESG Index and Multi-Factor Weighted Smart Beta Strategies

Prof. Amit Bathia
Assistant Professor, Finance and Accounting
NMIMS Anil Surendra Modi School of Commerce, Mumbai
Email: amit.bathia@nmims.edu

Mr. Preet Jain
Bachelors of Business Administration,
NMIMS Anil Surendra Modi School of Commerce, Mumbai, India
Email: preet.mj04@gmail.com

Ms. Soummyaa Salwan
Bachelors of Business Administration,
NMIMS Anil Surendra Modi School of Commerce, Mumbai, India
Email: soummyaasalwan@gmail.com

Ms. Kashvi Budhlani
Bachelors of Business Administration,
NMIMS Anil Surendra Modi School of Commerce, Mumbai, India
Email: kashvibudhlani22@gmail.com

Mr. Kaustubh Shrivastava
Bachelors of Business Administration,
NMIMS Anil Surendra Modi School of Commerce, Mumbai, India
Email: skaustubh420@gmail.com

Ms. Khushi Sharma
Bachelors of Business Administration,
NMIMS Anil Surendra Modi School of Commerce, Mumbai, India
Email: khushii.sharmaa65@gmail.com

Prof. Dr. Akshay Damani *
(*Corresponding Author)
Associate Dean and Associate Professor, Finance and Accounting
NMIMS Anil Surendra Modi School of Commerce, Mumbai
Email: akshay.damani@nmims.edu

Abstract

Smart Beta Investing Strategies have acquired momentum in emerging markets over the past decade; however, they have yet to be investigated in academia, and researchers are unable to provide empirical evidence. Previous research on the Indian equity markets and the clever beta strategies and factors has indicated that there is some optimism in the field. The authors augment the current corpus of research by employing an ESG-filtered index in conjunction with the conventional factors of value, size, and momentum to identify the ten most optimal stocks for each feasible portfolio configuration. A single factor and multi-factor weighting scheme are implemented to determine the ultimate portfolio and return. The Smart Beta portfolio exhibits superior returns when contrasted with its passive counterparts, as evidenced by statistical tools and risk-return characteristics. The absence of empirical evidence and a scarcity of data result in certain limitations for the study.

Keywords*:* Smart Beta, Smart Beta Investing, Passive Investing, Active Investing, Advanced Beta, Alternative Beta, Factor Investing, Alternative Risk Premium, Index Investing, ESG Funds, ESG Integration, NIFTY 100, NIFTY ESG 100 Index, Multi-factor Weighted Strategy, Equal Weighting, Mix Weighting, Integrated Weighting, Indian Equity Market

I. Introduction

In his influential book, 'The Innovator's Dilemma' (1997), Clayton Christensen delineates three distinct categories of innovation: disruptive, sustaining, and revolutionary. The objective of disruptive innovation in investment management is to improve investment outcomes and satisfy the requirements of investors, rather than merely accommodating their requests. The impetus for innovation is derived from a conviction that clients should allocate their investments, even if they are oblivious that a change is required.

Smart beta products represent a groundbreaking financial advancement that could greatly influence the operations of conventional active management. They offer a crucial element of active management through straightforward, clear, rules-based portfolios available at reduced costs (Kahn & Lennon, 2016). A smart beta strategy aims to achieve better returns and/or reduced risk after accounting for fees and expenses.

More than five decades ago, strategies for investment management were categorized into active and passive approaches. Active management involves investment experts striving to generate alpha by choosing specific securities, whereas passive management has become more popular as a strategy that emphasizes investing in the overall market by following a market-cap-weighted benchmark index. The growing popularity of index investing strategies, including smart beta, along with the introduction of new index-based products, has changed the understanding of active and passive management, making it harder to distinguish between the two.

The rising popularity of index investing coincides with a heightened desire for more personalized approaches in the investment journey. A recent report from MSCI highlights that "Generic, one-size-fits-all model portfolios are losing their appeal as investors seek more personalized investment solutions tailored to their unique needs and goals" (Ferenc and Lodh 2023). Factors specific to investors can include personal preferences, values, goals, and tax considerations. A study carried out by Charles Schwab Asset Management (2023) found that 88% of ETF investors want to enhance the personalization of their investment portfolios, and 78% aim to better align their investments with their personal values. Additionally, 74% expressed a preference for investments that are connected to a particular theme.

This focus on customization aligns with the growing interest among young investors in investment strategies that reflect their values. Fender and Munson (2022) note that there has been a rise in the popularity of ESG (Environmental, Social, Governance) investing among younger retail investors, with 67% either actively using ESG strategies or showing considerable interest in them. Furthermore, 68% of retail investors using ESG strategies reported that their reason for including ESG factors in their investment approach is to reflect personal values or to support companies that contribute positively to society or the environment. The growth of ESG investing is clear in the rising net assets of responsible investment funds around the world. The close connection between ESG investing and personalization suggests an increasing demand for products tailored to personal values and objectives.

The Boston Consulting Group's "Global Asset Management 2024" report indicates that Global Assets Under Management (AUM) are on the rise, aiming to hit a new record of $125 trillion by the close of 2024. Forecasts indicate that AUM is set to expand effectively and evolve, potentially hitting $150 trillion by 2027, driven by the rising embrace of technology and positive attitudes towards ESG factors.

Investment approaches that involve minimal active management, like index funds and ETFs, have seen a significant rise in favor owing to their reduced costs, heightened investor knowledge, and an expanding confidence in market efficiency. A significant portion of investments in passive funds that follow active indices is generated and overseen using smart beta or factor investment strategies. These strategies aim to blend the advantages of active investing, with the potential for generating alpha, while also ensuring the transparency and low costs associated with passive market index funds.

Active strategies have the ability to generate returns above the market average through hands-on management of investment portfolios. However, they depend on the judgment of fund managers, which can lead to a lack of clarity and typically involves elevated management fees and implementation expenses. Conversely, strategies that track passive market indices offer the advantages of affordability and clear execution. Nonetheless, one must accept market returns and give up the chance to achieve active returns. Investment strategies based on factors or their smart beta versions provide advantages such as active returns, cost-effectiveness, and clear execution.

II. Literature Review

In 1952, Harry Markowitz suggested that to accurately assess investment performance, it is crucial to consider risk and correlation alongside returns. He emphasized the importance of diversification in building a portfolio, which established the groundwork for Modern Portfolio Theory (MPT). This revolutionary claim significantly altered the approach to portfolio creation, leading to the development of 'efficient' portfolios that either optimize returns for a specific level of risk or reduce risk for a particular level of return. The 'optimal' portfolio represents the most effective among these efficient portfolios. According to his novel study, investors only needed to maintain a 'cap-weighted market portfolio,' which was viewed as the optimal mean-variance solution.

It is believed that investing in a market portfolio might be the best way to achieve a risk premium. In the following years, many researchers (Basu, 1977; Fama & French, 1993, 1996; Jegadeesh & Titman, 1993; Zhang, 2005; Hou et al., 2015) discovered different risk factor exposures such as value, size, profitability, investment and others that produced excess returns. Research has also shown that portfolios incorporating different risk factors can yield better returns than conventional market portfolios, suggesting that these market indices do not achieve mean-variance efficiency. Therefore, it is essential to create portfolios that are well-diversified and optimized for mean-variance, in addition to the traditional market portfolio.

Since the launch of the Capital Asset Pricing Model (CAPM) in 1960, the investment community has relied on traditional capitalization-weighted indices or CAPM for asset allocation models. While the original CAPM has faced significant scrutiny from later studies, it represented an important shift from focusing on the distinct features of individual securities to emphasizing systematic factors that reflect overall market risks and the relationships between different assets (Ang 2014).

Currently, market-cap-weighted indexes continue to serve as the foundational principle of index investing. The early discussions in the 1960s and 1970s raised the issue of whether fund managers had the ability to exceed market performance. Index investing emerged as investors changed their preferences, influenced by dominant academic ideas, to seek extensive market exposure rather than focusing on active management. Investors are now placing a greater emphasis on personalization in their investment journeys, prompting them to look for products and strategies that resonate with these objectives (CFA Institute Index Investing Report, 2024).

Due to the variations in conventional indices and the effects of ineffective stock markets, investors are increasingly seeking clear and rule-based indices that utilize non-market-cap weighting methods. These different weighted portfolios are referred to by terms such as 'advanced beta', 'smart beta', 'alternative beta', 'factor investing', and 'alternative risk premium', among others (Kudohet al., 2015; Blitz, 2016).

Smart beta investing is based on the following logic: the investor builds a portfolio that passively follows an index whose weights are independent from the market capitalization but reflect the exposure to some systematic factor (Alessandrini and Jondeau, 2019). The aim of these strategies is to reduce the fundamental weaknesses of conventional market indices, such as the tendency to favor overpriced stocks while neglecting those that are underpriced. This new approach to equity investing aims to tackle the limitations associated with high concentration and negative factor exposures found in traditional market indices. Smart beta indices seek to capitalize on rewarded risk premia factors while mitigating unrewarded risks through broadened weighting methods.

Arnott and Kose (2014) defined smart beta as a “category of valuation-indifferent strategies that consciously and deliberately break the link between the price of an asset and its weight in the portfolio, seeking to earn an excess return over cap-weighted benchmark by no longer weighing assets proportional to their popularity, while retaining most of the positive attributes of passive indexing.” It is a novel investing ideology that integrates underlying factors such as size, low risk, profitability, value, investment, and momentum (Basu, 1977). The notion has been supported and researched upon by academicians across the years as can be seen in the seminal work of Banz (1981), Jegadeesh & Titman (1993), Fama & French (1996, 2012, 2015), Frazzini & Peders-en (2014). BlackRock frequently refers to these funds as "the vehicle to deliver factor investing." In other words, smart beta strategies seek to outperform conventional passive indices by implementing a factor-based investment approach.

According to Jacobs and Levy (2014), smart beta investing combines active and passive investing strategies. They contended that these strategies are founded on a rule-based mindset that weighs equities differently than standard cap-weighting methodologies. These techniques are called active investing since they capture "risk premia factors" at a reduced cost, perhaps resulting in better solutions than traditional cap-weighted indices. These strategies, like passive investing, have qualities such as transparency and a rule-based systematic approach.

Ang et al. (2009) discovered that factor-driven smart beta strategies are gaining popularity since they are based on well-founded risk factors that significantly improve risk-adjusted performance. Factors are particular attributes that help explain the risks and returns of a collection of securities (Bender, Briand, Melas, & Subramanian 2013). There are hundreds of characteristics to consider, but the six most common are value, size, momentum, volatility, dividend yield, and quality. The CAPM was the first mainstream model used by investing professionals to explain stock returns, hence it is also known as a factor model.

The Fama-French (1993) three-factor model builds on the CAPM by concluding that the size and value factors, as well as the market return factor, can help explain stock returns. Carhart (1997) also created the Carhart four-factor model by adding the momentum element to the Fama-French three-factor models. Smart beta ETFs can incorporate a vast array of factors into their security selection and weighting strategies due to the proliferation of factors in recent years.
This allows investors to easily access a diverse selection of index-based strategies that increase exposure to specific factors relative to passive elements in the portfolio while reducing costs relative to active elements. Kahn and Lemmon (2016) discovered that smart beta products produce abnormal returns in a more cost-effective and transparent manner than actively managed products. Agarwal-la et al. (2017) investigated value, size, and momentum determinants in the Indian stock market from 1994 to 2017. They determined that while momentum and value are feasible assets, size does not beat the market portfolio in the Indian equities market. Between 1980 and 2015, Angelidis and Tessaromatis (2017) investigated four factor portfolios: value, low-risk, small-cap, and momentum, for 23 established and 21 emergent economies. They found that factor portfolios had statistically significant returns and higher Sharpe ratios than global market portfolios in the majority of cases. Additionally, the authors expanded their analysis by creating global factor portfolios that encompassed emerging economies, and they identified evidence of enhanced factor return efficiency.

Blitz (2016) analyzed the performance of smart beta strategies using two weighting methods and reported that these portfolios consistently outperformed the cap-weighted index from 1990 to 2015. Hanauer and Linhart (2015) investigated three factors: value, size, and momentum for 21 developing and 24 developed countries, discovering that the value component is more frequent in emerging economies than in developed markets. Cakici et al. (2013) investigated factor indices of value and momentum in 18 emerging markets, including Eastern Europe, Asia, and Latin America, and discovered considerable evidence for value and momentum effects in all emerging countries except Eastern Europe from January 1990 to December 2011.

The paper, ‘Is smart beta investing reaching its limits? An analysis of capacities, factor exposures and performance of smart beta ETFs’ by Mittertreiner (2019) investigates whether smart beta strategies are reaching their limits by analyzing capacities, factor exposures, and performance of smart beta ETFs from January 1993 to May 2018. The findings suggest that most smart beta strategies still have significant capacity for further growth. Additionally, the study finds no positive bias toward certain factors on the aggregate level, indicating that factor premiums are not being arbitraged away rapidly. This argues against the concern that smart beta investing is reaching its limits.

From April 2004 to March 2020, Monga et al. (2021) studied optimization-based alternative indexing techniques in India's growing equities market. They discovered evidence of significant outperformance and enhanced diversification for optimized methods when compared to the conventional market index. Diversification is extremely important in any asset class, including equity. Extreme concentration exposes investors to significant idiosyncratic risk since too much diversification can lead to 'diworsification,' or holding too many companies. The appropriate combination of smart beta and factor investment strategies can result in higher risk-adjusted returns. Creating the appropriate multi-factor investing plan is critical (Joshipura & Joshipura, 2023).
In the paper titled, 'How Smart are Smart-Beta Exchange Traded-Funds: Analysis of Relative Performance and Factor Exposure' (2016), Glushkow did not find any empirical evidence that smart beta funds, as a whole, benefit from contrarian trading after evaluating the claim of some smart beta advocates that periodic rule-based rebalancing is the primary reason why most smart beta strategies outperform. This is due to the fact that the dynamic allocation component does not consistently provide a significant positive contribution to the relative performance of smart beta ETFs. In certain instances, it significantly diminishes it. He determined that the primary factor driving smart beta ETF performance is static factor exposure, rather than systematic rebalancing to target non-cap weights, as indicated by the results of the performance attribution analysis.

Strong empirical evidence indicates that clever beta tactics are effective. Nevertheless, the literature is predominantly restricted to the United States and other mature markets. These investment strategies may or may not be effective in a swiftly expanding market such as India. The current study concentrates on the design, implementation, and performance of smart beta investments in the unexplored, expanding Indian equities market, due to the scarcity of such empirical information.

The study, 'Smarter Beta Investing: More Focus, Less Sustainability Bias, Same Performance' by Bailer & Miller (2024) demonstrates how smart beta indices, tilted towards Size, Quality, Value, and other factors, can be replicated, and customized to address inherent negative sustainability biases while maintaining the Sharpe ratio. Using the MSCI Barra Portfolio Manager platform, the core MSCI World Factor Tilt indices are replicated and analyzed. Integrating sustainable constraints effectively mitigated negative biases across the eight factor-tilt portfolios that the researchers chose, while preserving their target tilts and Sharpe ratios.

ESG integration has replaced screening as the primary investment method. Factor investing in the ESG domain is generally done through quantitative ESG integration solutions. A common approach is to begin with an ESG-filtered investing universe and then develop a multifactor strategy in which ESG features are either directly integrated as an ESG factor or indirectly as limitations in portfolio creation (Ang, 2020). In 2019, Alessandrini and Jondeau in their paper titled 'ESG Investing: From Sin Stocks to Smart Beta', concluded that the ESG profile of passive investment and smart beta strategies can be improved without deteriorating risk-return performances for most regions and for most ESG criteria. Their analysis and findings indicate that the popular smart beta approaches would have benefited from an ESG screening over the period. Even with aggressive exclusions, the targeted factors would remain in place. Although there is some reduction in the exposure to the targeted factor, it appears to be compensated by an increase in the ESG profile of the portfolio. Bathia et al. (2024) found that ESG Schemes are attracting more investments during the period under study however, the returns on all the schemes have not been higher than returns on the market. **This research adds to the increasing literature by revealing the existence and effective implementation of ESG-filtered multi-factor weighted smart beta strategies in an emerging financial market.**

III. Research Objectives

This paper attempts to improve understanding of the subject area by aiming to:

- Understand the Smart Beta Investing Strategy from the perspective of ESG considerations by selecting a market-capitalization-weighted index on the lines of ESG factors (stock universe)

- Decode the impact of the traditional factors, i.e Value, Size and Momentum, when applied as a filter to the NIFTY 100 ESG Index constituents, thereby combining a contemporary factor (ESG) with the traditional factors.
- Decode the impact of weighting strategies by employing a single-factor weighting strategy (Equal Weighting) vis-à-vis the multi-factor weighting strategies, comprising Mix, Integrated and Sequential Weighting processes.

IV. Hypothesis

Hypothesis A:

- H0: The returns generated by the NIFTY 100 ESG Index are not superior than the traditional NIFTY 100 Index

Hypothesis B:

- H0: When the Smart Beta Strategy is applied to the NIFTY 100 ESG Index, the returns generated are not superior to when the normal NIFTY 100 ESG Index is used.

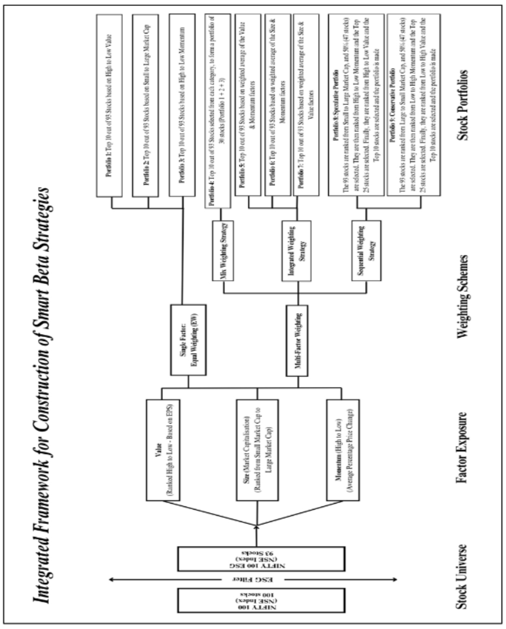
Hypothesis C:

- H0: When the Smart Beta Strategies are applied to the NIFTY 100 ESG Index, the multifactor strategies do not generate superior returns to the single-factor strategies.

V. Research Methodology

The research encompasses a quantitative analysis of secondary data, comprising companies listed on the Nifty100 ESG Index, with the stock universe having undergone ESG filtering prior to factor exposure. This research focuses on three specific factor-based smart beta exposures: size, value, and momentum, which are collectively referred to as elements of the Carhart's Four-Factor Model alongside market risk. Following the selection of stocks based on the identified factors, two distinct weighting schemes have been implemented: equal weighting and multi-factor weighting. The latter encompasses three sub-categories: the Mix approach, Integrated approach, and Sequential Approach, which are utilized for the purpose of ranking and calculating stock returns alongside other pertinent analytical measures. The subsequent sections of this document provide a detailed explanation of the implementation of this procedure.

V.I. Visual Representation of the Framework Utilized



(Idea adapted from Monga, R., Aggrawal, D., & Singh, J. (2022). Smart Beta Investing: An Alternative Investment Paradigm in Emerging Indian Equity Market. This diagram has been adapted and modified here by the Authors for this research)

V.II. Selection of Index and ESG Integration

For the research, the NIFTY 100 Index was considered as the ideal base index over the other indices due to the following factors:

- NIFTY 100 offers a comprehensive overview of the top 100 companies listed on the NSE, providing a broader and more diversified representation of the Indian market and therefore broader datasets, which offer more nuanced insights into factor-based performance.
- A wider index like the NIFTY 100 enables us to capture greater sectoral diversity and a broader range of company sizes (large and mid-cap). This is critical for effectively capturing the impact of factors such as value, momentum, and size.
- Applying ESG filters on the NIFTY 100 offers a stronger foundation for building multi-dimensional portfolios, integrating both financial and non-financial metrics.

The integration of ESG (Environmental, Social, and Governance) factors adds an innovative dimension to the smart beta investing strategy for several reasons:

- A research gap was identified in the paper *"Smart Beta Investing: An Alternative Investment Paradigm in Emerging Indian Equity Market."* The paper highlighted the lack of ESG focus in smart beta studies in India, motivating the authors to address this gap. By incorporating ESG factors into the analysis, the authors aim to contribute novel insights and expand the existing research on sustainable and responsible investing.
- ESG has emerged as a mainstream investment criterion, with investors increasingly favoring sustainable and responsible investing.
- The application of ESG filters within the NIFTY 100 index allows us to assess how companies with higher ESG scores perform compared to others. This combination of non-traditional (ESG) and traditional factors (value, momentum, size) provides novel insights for constructing multi-factor portfolios.
- ESG integration also opens pathways for further research, especially in emerging markets like India, where sustainable investing is gaining momentum. Additionally, it creates opportunities for exploring ESG-aligned smart beta strategies across different asset classes and geographic regions, providing an innovative approach to portfolio management.

V.III. Selection of Factor Exposure

In the research, the authors decided to focus on the Size, Momentum, and Value factors to stay aligned with Cahart's Four-Factor Model, which has been widely recognized in finance for explaining stock returns. By selecting just these three factors, the authors intend to create a more manageable and focused study while still capturing essential market behaviors. Size, Momentum, and Value are well-established in both academic and practical investing circles as key drivers of performance. This narrowed approach helps us dive deeper into these specific factors without complicating the analysis or diluting the findings by including less relevant or newer factors. This way, the authors strive to stay true to proven research while making the research outcomes more precise and achievable.

- **Value:** The companies are ranked from High Value to Low Value on the basis of EPS and the top 10 are selected for the portfolio and weight allocation.
- **Size:** Companies are ranked from Low Market Capitalisation to High Market Capitalisation on the basis of their full market capitalization.
- **Momentum:** The top 10 stocks are selected as per average percentage change in the price of stock.

V.IV. Weight Allocation

- **Equal Weighting:** This strategy is perceived as the 'Maximum Deconcentration' strategy and considers only one parameter - number of stocks (Monga and Singh, 2022). It mitigates the dominance of large-cap stocks therefore placing equal importance on all assets. The weight is calculated as per Equation (1)

$$\mathbf{W} = \frac{\mathbf{1}}{\boldsymbol{n}} \quad \ldots\ldots\ldots\ldots.. \quad (1)$$

where, ‘n’ is the number of stocks

Herein, three different portfolios [Portfolio - 1, 2 and 3] for each factor (value, size and momentum) have been formulated and assigned equal weightage to each stock in each portfolio. The number of stocks (10 stocks) in the portfolio is as per factor rankings as explained in Section V.III.

Weighted return was calculated using Equation (2) and Standard Deviation was performed for the same to ascertain the volatility of the portfolio.

$$\textbf{Weighted Return} = \boldsymbol{W} \times \boldsymbol{R} \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad (2)$$

where, W=Weight
R=Return

The authors also calculated the square of difference of returns and weighted returns which helped arrive at the Sortino’s ratio [Equation (3)]. Sortino’s ratio measures portfolio’s return over the risk-free rate in terms of downside deviation.

$$\textbf{Sortino's Ratio} = \sqrt{\frac{\Sigma(\boldsymbol{Return} - \boldsymbol{Weighted\ Return})^{2}}{\mathbf{12}}} \quad \ldots\ldots.. \quad (3)$$

- **Multi-Factor Weighting:** The study employed three distinct methods for constructing a multi-factor portfolio: mix, integrated, and sequential approaches. The choice of mix, integrate, and sequential multifactor strategies in the context of multi-factor investing stems from each strategy's unique advantages and ability to address specific investment goals and constraints.

  These three approaches—mix, integrate, and sequential—are popular for their distinct benefits in addressing factor-specific goals, and they allow portfolio managers to tailor exposure to meet varying investor needs and constraints (Joshipura, 2023).

  - **Mix Weighting:** This approach entails the development of a consolidated portfolio [Portfolio 4] that integrates the leading ten stocks from each factor, with weights assigned in accordance with the overall number of stocks present in this unified portfolio. A common portfolio was constructed utilizing the top ten stocks based on value, size, and momentum factors. Finally, the analysis involved the computation of weighted returns, the square of the difference between actual and weighted returns, standard deviation, and Sortino’s ratio. The Mix Approach maintains individual factor purity by separately allocating funds to pure-factor portfolios like value or momentum, providing distinct exposure and diversification benefits without blending factors excessively.

  - **Integrated Weighting:** This approach effectively addresses the problem of conflating pure-factor portfolios that exhibit extreme factor characteristics. Three multi-factor portfolios were constructed, selecting stocks that exhibited strong performance on an aggregate basis. The three portfolios were developed utilizing the following factor pairs:
    - Portfolio 5: Value and Momentum
    - Portfolio 6: Size and Momentum
    - Portfolio 7: Value and Size
      The subsequent step involved the calculation of weighted returns, the square of the difference between actual and weighted returns, standard deviation, and Sortino’s ratio. The Integrated Approach selects stocks that score well across multiple factors, aiming to capture ‘all-rounder’ stocks with balanced performance.

Sequential Weighting: The Sequential Strategy in multi-factor investing applies factors in a specific order to refine the stock selection process. Sequential Screening applies factors progressively (e.g., screening first for momentum, then for low volatility) to achieve specific, layered outcomes, providing flexibility and precise factor alignment to meet diverse investor goals, helping in targeting specific investment goals.

An example of sequential screening might start with a focus on low volatility to ensure stability, then apply secondary filters like momentum and then value to further optimize portfolio attributes. This multi-step screening increases turnover and implementation costs but can deliver a portfolio more closely aligned with investor goals. 93 companies from Nifty 100 ESG index were selected, and were equally divided into two groups (50-50%), large cap and small cap companies. Out of those 47 companies, 25 companies were selected for secondary filtering i.e. momentum and then finally, 10 companies were chosen according to the value factor and these constituted the final portfolio.

In terms of portfolio construction, the sequential strategy allows for categorization into Conservative and Speculative Groups:

1. Conservative Portfolio: This group is derived from stocks that score well across factors like low volatility, strong momentum, and high value. Stocks are filtered to prioritize stability and value, producing a portfolio that is expected to outperform due to its low-risk, high-value attributes.

2. Speculative Portfolio: In contrast, speculative portfolios include stocks with high volatility, weak momentum, and low value, leading to higher risk and, historically, lower returns.

The implication of these groupings is that conservative portfolios, with their lower risk and higher quality factor exposures, typically outperform speculative portfolios over the long term. They offer superior return-to-risk ratios, making them attractive for risk-averse investors. Meanwhile, speculative portfolios are more suited for investors willing to accept higher volatility in exchange for potential high short-term gains but at a lower return-to-risk ratio over time. Subsequently, the weighted return, standard deviation, and Sortino's ratio were computed for these stocks.

V.V. Linear Regression

Regression was conducted through the Jamovi statistical software on the following variables:

- Dependent Variable: Return
- Independent Variable:
  - Size Factor (Market Capitalization)
  - Value Factor (EPS)
  - Momentum Factor (Average % Change in Price)

Regression analysis aligns with the concept of factor investing and its insights can be used to construct portfolios that are tilted towards value, size, or momentum factors, or a combination of these. The authors chose variables in line with the Carhart (1997) Four Factor Model which consists of SMB (Size - Small Minus Big), WML (Momentum - Winners Minus Losers), and HML (Value - High Minus Low).

V.VI. Use of Formulas for Data Analysis

Specific performance and risk metrics were utilized to ensure a comprehensive evaluation of factor-based portfolios. Each metric plays a distinct role in assessing the return, risk, and overall efficiency of the strategies employed. Following is the rationale for using each metric/formula:

- **Weighted Return** measures the portfolio's overall return by accounting for the weights assigned to individual assets. In smart beta strategies, factors like value, momentum, and size drive the selection and weighting of stocks, making this metric essential for evaluating the performance based on these factor allocations.

- **Volatility** quantifies the degree of price fluctuations over a specific period, representing the total risk. Understanding the volatility of factor-based portfolios is crucial, as these strategies seek to balance returns with lower risk exposure.
- **Sharpe Ratio (Risk-Free)** measures the risk-adjusted return by comparing excess returns to total volatility. It helps determine whether the smart beta portfolio delivers superior returns for the risks taken.
- **Sharpe Ratio (NIFTY 100 ESG)** compares portfolio performance against the NIFTY 100 ESG index as the benchmark. Including the NIFTY 100 ESG filter aligns with the ESG-driven component of our study, showing how sustainable investing factors impact risk-adjusted returns.
- **Relative Return** evaluates the portfolio's performance relative to a benchmark (e.g., NIFTY 100). Smart beta strategies aim to outperform traditional benchmarks. This metric allows us to quantify whether our factor-based portfolio achieves that goal.
- **Tracking Error** measures the deviation of portfolio returns from the benchmark. It is useful for evaluating active management in smart beta strategies and understanding how closely the portfolio follows or diverges from the benchmark performance.
- **R^2 (R-Squared)** indicates the proportion of portfolio returns explained by movements in the benchmark index. A higher R^2 suggests that the portfolio's performance is highly correlated with the benchmark, while a lower value indicates a unique strategy that may add diversification benefits.
- **Sortino Ratio** focuses on the risk-adjusted return but penalizes only downside volatility, unlike the Sharpe Ratio. It is particularly valuable for smart beta strategies, where minimizing downside risks while achieving superior returns is a key objective.

These metrics provide a well-rounded perspective on performance and risk management, aligning with the objectives of smart beta investing, which aims to achieve above-market returns with optimized risks. Together, they help evaluate how factor-based portfolios behave under different market conditions, assess the effectiveness of ESG integration, and analyze deviations from traditional benchmarks.

VI. Data Analysis and Findings

The considered smart beta strategies incorporate three factor exposures across the various weighting schemes. The Absolute Performance of the different factors in the Equal Weighting Strategy is summarized in Tables 1, 2, and 3 respectively. Each table takes into consideration only one factor, either value, or size, or momentum, which is in line with the single-factor weighting adopted. *(The following tables and figures have been computed by the authors using statistical analysis as per the methodology given above. Datasets utilized have been provided in the Annexures)*

Table 1: Evaluating the risk-return profile of Portfolio 1 (based on Value factor only and single-factor equal weighted method) vis-a-vis the NIFTY100 ESG and NIFTY 100 Index

Metrics	Equal	NIFTY100 ESG	NIFTY 100
Weighted Return	59.47%	39.40%	38.50%
Volatility	4.98%	13.14%	13.80%
Sharpe Ratio (Risk Free)	10.47	2.44	2.26
Sharpe Ratio (Nifty100 ESG)	4.03	2.44	2.26
Relative Return	7.07	4.35	4.23
Tracking Error	1.47%	-	-
R^2	0.00048	-	-
Sortino Ratio	0.62	-	-

Table 2: Evaluating the risk-return profile of Portfolio 2 (based on Size factor only and single-factor equal weighted method) vis-a-vis the NIFTY100 ESG and NIFTY 100 Index

Metrics	Equal	NIFTY100 ESG	NIFTY 100
Weighted Return	41.64%	39.40%	38.50%
Volatility	3.02%	13.14%	13.80%
Sharpe Ratio (Risk Free)	11.35	2.44	2.26
Sharpe Ratio (Nifty100 ESG)	0.74	2.44	2.26
Relative Return	4.65	4.35	4.23
Tracking Error	2.71%	-	-
R^2	0.0014	-	-
Sortino Ratio	0.42	-	-

Table 3: Evaluating the risk-return profile of Portfolio 3 (based on Momentum factor only and single-factor equal weighted method) vis-a-vis the NIFTY100 ESG and NIFTY 100 Index

Metrics	Equal	NIFTY100 ESG	NIFTY 100
Weighted Return	83.36%	39.40%	38.50%
Volatility	7.64%	13.14%	13.80%
Sharpe Ratio (Risk Free)	9.95	2.44	2.26
Sharpe Ratio (Nifty100 ESG)	5.76	2.44	2.26
Relative Return	10.32	4.35	4.23
Tracking Error	5.72%	-	-
R^2	0.04434	-	-
Sortino Ratio	0.91	-	-

The results indicate that the Smart Beta Indices have outperformed the market index, as the Weighted Return, Sharpe Ratio, and Sortino Ratio are substantially higher for smart beta.

- A higher Sharpe Ratio indicates a better return relative to the amount of risk taken. (>1.0: A good or acceptable ratio, >2.0: A very good ratio, >3.0: An excellent ratio, <1.0: A sub-optimal ratio).
- A higher Sortino ratio indicates a better risk-adjusted return. This means the investment generated higher returns relative to the downside risk it faced.
- A government bond rate or risk-free rate of 7.365% served as the Sharpe Ratio (Risk-Free) benchmark. The 10-year government yield of India is frequently employed as a substitute for the risk-free rate. The Nifty100 ESG Return served as the benchmark for the Sharpe ratio (Nifty100 ESG).
- Tracking Error is a measure of how closely an investment's performance follows its benchmark index. It quantifies the deviation between the investment's returns and the benchmark's returns. TE is the highest for momentum strategy and and the lowest for value strategy. A higher tracking error indicates a larger deviation from the benchmark. This means the investment's performance is less correlated with the benchmark and vice-versa.

- Lower volatility in smart beta indexes as compared to market indexes indicate lower risk and a positive R^2 indicate that the performance of smart beta index is in line with that of the market. It is evident from Table 3 that the momentum strategy offers the highest R^2 factor.

Table 4: Evaluating the risk-return profile of Portfolio 4 (based on multi-factor weighted integration strategy and Value-Momentum factor pair) vis-a-vis the NIFTY100 ESG and NIFTY 100 Index

Multi-Factor Weighting Strategy			
Integrated Strategy - Value & Momentum			
Metrics	**Value - Momentum**	**NIFTY100 ESG**	**NIFTY 100**
Weighted Return	62.91%	39.40%	38.50%
Volatility	3.77%	13.14%	13.80%
Sharpe Ratio	14.75	2.44	2.26
Sortino Ratio	0.59	-	-
Tracking Error	1.96%	-	-

Table 5: Evaluating the risk-return profile of Portfolio 5 (based on multi-factor weighted integration strategy and Size-Momentum factor pair) vis-a-vis the NIFTY100 ESG and NIFTY 100 Index

Multi-Factor Weighting Strategy			
Integrated Strategy - Size & Momentum			
Metrics	**Size - Momentum**	**NIFTY100 ESG**	**NIFTY 100**
Weighted Return	61.88%	39.40%	38.50%
Volatility	3.15%	13.14%	13.80%
Sharpe Ratio	17.32	2.44	2.26
Sortino Ratio	0.56	-	-
Tracking Error	3.79%	-	-

Table 6: Evaluating the risk-return profile of Portfolio 6 (based on multi-factor weighted integration strategy and Size-Value factor pair) vis-a-vis the NIFTY100 ESG and NIFTY 100 Index

Multi-Factor Weighting Strategy			
Integrated Strategy - Size & Value			
Metrics	**Size - Value**	**NIFTY100 ESG**	**NIFTY 100**
Weighted Return	75.00%	39.40%	38.50%
Volatility	3.43%	13.14%	13.80%
Sharpe Ratio	19.7	2.44	2.26
Sortino Ratio	0.67	-	-
Tracking Error	1.48%	-	-

Table 7: Evaluating the risk-return profile of Portfolio 7(based on multi-factor weighted integration strategy and Size, Value and Momentum factors) vis-a-vis the NIFTY100 ESG and NIFTY 100 Index

Multi-Factor Weighting Strategy			
Mix Strategy			
Metrics	**MIX**	**NIFTY100 ESG**	**NIFTY 100**
Weighted Return	61.49%	39.40%	38.50%
Volatility	1.88%	13.14%	13.80%
Sharpe Ratio	0.88	2.44	2.26
Sortino Ratio	1.26	-	-
Tracking Error	1.25%	-	-

Table 8: Evaluating the risk-return profile of Portfolio 8 (based on multi-factor weighted sequential (speculative) strategy) vis-a-vis the NIFTY100 ESG and NIFTY100 Index

Multi-Factor Weighting Strategy			
Sequential Strategy			
Metrics	**SEQUENTIAL (speculative)**	**NIFTY100 ESG**	**NIFTY 100**
Weighted Return	3.73%	39.40%	38.50%
Volatility	2.63%	13.14%	13.80%
Sharpe Ratio	-0.97	2.44	2.26
Sortino Ratio	0.37	-	-
Tracking Error	2.12%	-	-

Table 9: Evaluating the risk-return profile of Portfolio 9 (based on multi-factor weighted sequential (conservative) strategy) vis-a-vis the NIFTY100 ESG and NIFTY100 Index

Multi-Factor Weighting Strategy			
Sequential Strategy			
Metrics	**SEQUENTIAL (conservative)**	**NIFTY100 ESG**	**NIFTY 100**
Weighted Return	5.70%	39.40%	38.50%
Volatility	4.71%	13.14%	13.80%
Sharpe Ratio	-0.29	2.44	2.26
Sortino Ratio	0.6	-	-
Tracking Error	1.78%	-	-

Tables 4 to 9 indicate that the smart beta indexes are outperforming the market indexes in the multi-factor weighting strategy (for all, integrated, mix, and sequential) due to the fact that the weighted return, Sharpe ratio, and Sortino ratio are all higher than those of the market. The smart beta indexes for the multi-factor model also suggest a reduction in volatility, which implies a reduced risk. Tracking error of most of the multifactor strategies is around 2%, indicating that an investment's performance closely follows its benchmark index.

Table 10: Linear Regression (Regressing Returns on EPS, Market Capitalisation, Average Percentage Change in Price)

Predictor	Estimate	SE	Lower	Upper	t	p
Intercept	0.40133	0.1037	0.19528	0.60738	3.87012	0.00021
EPS	0.00005	0.00032	-0.0006	0.00069	0.14392	0.88589

Mkt Cap	0.00005	0.00008	-0.0001	0.0002	0.61669	0.53901
Avg % change in Price	6.67151	3.19156	0.32995	13.01308	2.09036	0.03944

From Table 10, we can form the following regression equation:

Y = 0.40133+ 0.00005 EPS + 0.00005 * Mkt Cap + 6.67151 * Average % Change*

Where,

- 0.40133 is the intercept, which represents the expected value of Y when all other independent variables are 0
- The coefficient of EPS, Mkt Cap and Avg % Change in Price is 0.00005, 0.00005 and 6.67161 respectively, meaning that for every 1 unit increase in EPS, Mkt Cap and Avg % Change in Price holding the other variables constant, the dependent variable Y increases by 0.00005, 0.00005 and 6.67161 respectively.
- The t-values measure the significance of each predictor, and the corresponding p-values show whether they are statistically significant. Only Average % Change has a p-value below 0.05, indicating it is the only significant predictor in the model.

Table 11: Individual Factor Coefficient of Determination

	Value	Size	Momentum
R^2	0.00048	0.0014	0.04434

From Table 11, we can see that momentum has the strongest relationship with returns while size has the weakest relationship with returns. The value for adjusted R^2 is 0.01661. From the above estimates, Smart beta strategies that are incorporated using multiple factors as well as individual factors can consistently outperform traditional market cap weighted indices in terms of risk adjusted returns.

Table 12: Overall Coefficient of Determination

R^2	**0.04868**

From Table A lower R^2 suggests a weaker relationship between the independent variables and the dependent variable. Therefore, from Table 12, we see the individual R^2 to find which independent variable has a strong relationship with the dependent variable.

Hypothesis Analysis:

- Hypothesis A: We reject the Null Hypothesis (H0). Therefore, the returns generated by the NIFTY 100 ESG Index are superior to the traditional NIFTY 100 Index.

- Hypothesis B: We reject the Null Hypothesis (H0). Therefore, when the Smart Beta Strategy is applied to the NIFTY 100 ESG Index, the returns generated are superior to when the normal NIFTY 100 ESG Index is used.

- Hypothesis C: We reject the Null Hypothesis (H0). Therefore, when the Smart Beta Strategies are applied to the NIFTY 100 ESG Index, the multifactor strategies generate superior returns to the single-factor strategies.

VII. Conclusion

In the form of alternative weighting or selection criteria that deviate from traditional benchmarking, new index-based products, such as smart beta ETFs and direct indexing, incorporate active decision making. Consequently, smart beta has the potential to produce excess returns that surpass a cap-weighted benchmark. To put it simply, investors can enjoy the advantages of traditional passive management and systematically invest in the market while taking advantage of opportunities to outperform it. Furthermore, these products allow investors to pursue their own investment approaches or values.

VIII. Limitations and Future Scope

Limitations:

- The Sharpe ratio, which measures risk, does not effectively capture downside risk. This limits the accuracy of risk assessments.
- The Sortino ratio focuses solely on downside risk, neglecting the upside potential of an investment. This can be a limitation for investors who are interested in both risk and return.
- Smart beta strategies can result in tracking errors when they don't align perfectly with benchmarks. Tracking error alone is insufficient to gauge a fund's performance.
- Factor-based strategies often rely on historical data. If the historical relationships between factors and returns change, these strategies may underperform.
- The regression of EPS and returns was found to be insignificant, suggesting the need for a better proxy for value like P/E ratio and P/B ratio.

One potential area of investigation for future research is the implementation of smart beta investing in various asset classes (such as commodities, fixed income, real estate) and other emerging markets. In addition, it is strongly recommended that the risk-return analysis of various multi-factor portfolios be conducted using the other three traditional factors: quality, profitability, and investment. It would be intriguing to observe the top-down (broader, macro level) and bottom-up (individual stocks) methodologies for developing smart beta strategies. Additionally, the incorporation of new dimensions of smart beta investing, such as the consolidation of DEI rankings and other robust popular qualitative factors, could serve as a significant and innovative criterion for future research. Furthermore, as the popularity of ESG Investing grows, the effect of the herd mentality bias can also be explored.

References

Data Sources

1. Investing.com. (2026). Investing.com [Dataset]. https://www.investing.com/
2. NSE. (2024a). Market Watch - Equity/Stock [Dataset; Online]. NSE India. https://www.nseindia.com/market-data/live-equity-market?symbol=NIFTY%20100
3. NSE. (2024b). NIFTY 100 ESG [Dataset; Online]. NSE India Indices. https://www.niftyindices.com/indices/equity/thematic-indices/nifty100-esg
4. NSE. (2025). NSE Indexogram NIFTY 100. In NSE India Indices. NSE India. https://www.niftyindices.com/Factsheet/ind_nifty_100.pdf
5. NSE India. (2024a). NIFTY 100. NSE Indices. https://www.niftyindices.com/indices/equity/broad-based-indices/nifty-100
6. NSE India. (2024b). NSE 100 ESG Indices Methodology Document. In NSE. https://archives.nseindia.com/content/indices/Method_NIFTY100_ESG_Indices.pdf
7. NSE India. (2024c). NSE Indexogram. In NSE India. https://www.niftyindices.com/Factsheet/Factsheet_NIFTY100_ESG_Index.pdf
8. Screener. (2024). NIFTY 100 ESG [Dataset]. https://www.screener.in/company/NIFT100ESG/

Academic References

1. Agarwalla, S. K., Jacob, J., & Varma, J. R. (2017). Size, Value, and Momentum in Indian Equities. Vikalpa the Journal for Decision Makers, 42(4), 211–219. https://doi.org/10.1177/0256090917733848
2. Alessandrini, F., & Jondeau, E. (2020). ESG Investing: From Sin Stocks to Smart Beta. The Journal of Portfolio Management, 46(3), 75–94. https://doi.org/10.3905/jpm.2020.46.3.075
3. Amenc, N., Goltz, F., & Lodh, A. (2012). Choose Your Betas: Benchmarking AlternativeEquity Index Strategies. The Journal of Portfolio Management, 39(1), 88–111. https://doi.org/10.3905/jpm.2012.39.1.088

4. Ang, A. (2014). Asset Management. https://doi.org/10.1093/acprof:oso/9780199959327.001.0001
5. Ang, A., Goetzmann, W. N., & Schaefer, S. M. (2009). Evaluation of Active Management of the Norwegian Government Pension Fund – Global. https://www0.gsb.columbia.edu/faculty/aang/papers/report%20Norway.pdf
6. Angelidis, T., & Tessaromatis, N. (2017). Global Equity Country Allocation: An Application of Factor Investing. Financial Analysts Journal, 73(4), 55–73. https://doi.org/10.2469/faj.v73.n4.7
7. Arnott, R. D., & Kose, E. (2014). What "Smart Beta" Means to Us. Research Affiliates. Retrieved September 15, 2024, from https://www.researchaffiliates.com/en_us/publications/articles/292_%20what_smart_beta_means_to_us.html.
8. Bailer, H., & Miller, J. (n.d.). Smarter Beta Investing: More Focus, Less Sustainability Bias, Same Performance.
9. Basu, S. (1977). Investment Performance of Common Stocks in relation to their Price-Earnings Ratios: A Test of the Efficient Market Hypothesis. The Journal of Finance, 32(3), 663–682. https://doi.org/10.1111/j.1540-6261.1977.tb01979.x

10. Bathia, A., Manjrekar, J., & Padhy, J. (2024). Are Indian ESG Funds Sustainable? Journal of Informatics Education and Research, 4(2).
11. https://doi.org/10.52783/jier.v4i2.930
12. Bender, J., Briand, R., Melas, D., & Subramanian, R. A. (2012). Foundations of Factor Investing. In MSCI. MSCI Index Research. Retrieved September 15, 2024, from https://www.msci.com/ documents/10199/71b6daf5-9e76-45ff-9f62-dc2fcd8f2721
13. Blitz, D. (2016). Factor Investing with Smart Beta Indices. The Journal of Index Investing, 7(3), 43–48. https://doi.org/10.3905/jii.2016.7.3.043
14. Boston Consulting Group. (2024). AI and the Next Wave of Transformation. In Global Asset Management Report.
15. Cakici, N., Fabozzi, F. J., & Tan, S. (2013). Size, value, and momentum in emerging market stock returns. Emerging Markets Review, 16, 46–65. https://doi.org/10.1016/j.ememar.2013.03.001
16. Carhart, M. M. (1997). On Persistence in Mutual Fund Performance. The Journal of Finance, 52(1), 57–82. https://doi.org/10.1111/j.1540-6261.1997.tb03808.x
17. Charles Schwab Corporation. (2023). Annual Report on Asset Management. In Charles Schwab. https://content.schwab.com/web/retail/public/about-schwab/schwab_annual_report_2023.pdf
18. Doyle, J., & Hayman, G. (2024). Smart Beta, Direct Indexing, and Index-Based Investment Strategies: A Framework. In CFA Institute Research & Policy Center. https://doi.org/10.56227/24.1.16
19. Factor investing insights | BlackRock. (n.d.). BlackRock. https://www.blackrock.com/us/individual/investment-ideas/what-is-factor-investing/factor-commentary/andrews-angle/esg-in-factors
20. Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. Journal of Financial Economics, 33(1), 3–56. https://doi.org/10.1016/0304-405x(93)90023-5
21. Fama, E. F., & French, K. R. (1996). Multifactor Explanations of Asset Pricing Anomalies. The Journal of Finance, 51(1), 55–84. https://doi.org/10.1111/j.1540-6261.1996.tb05202.x
22. Fama, E. F., & French, K. R. (2012). Size, value, and momentum in international stock returns. Journal of Financial Economics, 105(3), 457–472. https://doi.org/10.1016/j.jfineco.2012.05.011
23. Fender, R., & Munson, R. (2022). Enhancing Investors' Trust: 2022 CFA Institute Investor Trust Study. https://doi.org/10.56227/22.1.18
24. Glushkov, D. & Investment Management Consultants Association Inc. (2016). How Smart Are Smart Beta Exchange-Traded Funds: Analysis of Relative Performance and Factor Exposure. In Journal of Investing Consulting.
25. Hanauer, M. X., & Linhart, M. (2015). Size, Value, and Momentum in Emerging Market Stock Returns: Integrated or Segmented Pricing? Asia-Pacific Journal of Financial Studies, 44(2), 175–214. https://doi.org/10.1111/ajfs.12086
26. Hou, K., Xue, C., & Zhang, L. (2014). Digesting Anomalies: An Investment Approach. Review of Financial Studies, 28(3), 650–705. https://doi.org/10.1093/rfs/hhu068
27. Jacobs, B., & Levy, K. (2014). Smart Beta versus Smart Alpha. The Journal of Portfolio Management, 40(4), 4–7. https://doi.org/10.3905/jpm.2014.40.4.004

28. Jegadeesh, N., & Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. The Journal of Finance, 48(1), 65–91. https://doi.org/10.1111/j.1540-6261.1993.tb04702.x
29. Joshipura, M. (Ed.). (2023). Smart Beta Investing: The Cornerstone of Systematic Active Investing (1st ed., Vols. 1–1) [Digital PDF]. Imperial Publications. https://sbm.nmims.edu/docs/2024/Smart-Beta-Investing-Book-Final.pdf
30. ISBN 978-93-91044-43-5
31. Kahn, R. N., & Lemmon, M. (2016). The Asset Manager's Dilemma: How Smart Beta Is Disrupting the Investment Management Industry. Financial Analysts Journal, 72(1), 15–20. https://doi.org/10.2469/faj.v72.n1.1
32. Kudoh, H., Miazzi, A., & Yamada, T. (2015). The Low-Correlation Enhancement: How to Make Alternative Beta Smarter. The Journal of Investing, 24(4), 81–91. https://doi.org/10.3905/joi.2015.24.4.081
33. Markowitz, H. (1952). Portfolio Selection. The Journal of Finance, 7(1), 77–91. https://doi.org/10.1111/j.1540-6261.1952.tb01525.x
34. Monga, R., Aggrawal, D., & Singh, J. (2021). Exploring new frontiers in indexing strategies: an optimization-based risk-efficient solution. International Journal of Systems Assurance Engineering and Management, 13(S2), 853–865. https://doi.org/10.1007/s13198-021-01138-3
35. Monga, R., Aggrawal, D., & Singh, J. (2022). Smart Beta Investing: An Alternative Investment Paradigm in Emerging Indian Equity Market. Organizations and Markets in Emerging Economies, 13(1), 209–237. https://doi.org/10.15388/omee.2022.13.77
36. Zhang, L. (2005). The Value Premium. The Journal of Finance, 60(1), 67–103. https://doi.org/10.1111/j.1540-6261.2005.00725.x

Annexures

Annexure 1: Factor Ranking Data

1.1. Value Factor: Portfolio - 1

Companies	EPS	Rank	Companies	EPS	Rank	Companies	EPS	Rank
BOSCHLTD	863.58	1	CIPLA	53.3	37	POWERGRID	16.88	73
BAJAJHLDNG	670.49	2	ASIANPAINT	52.96	38	AMBUJACEM	15.56	74
SHREECEM	582.59	3	BAJAJFINSV	52.28	39	IRCTC	14.83	75
MARUTI	472.62	4	COLPAL	51.99	40	MARICO	11.73	76
DRREDDY	333.63	5	TORNTPHARM	51.27	41	TATAPOWER	11.56	77
BAJAJ-AUTO	284.77	6	NAUKRI	50.22	42	M	11.52	78
ULTRACEMCO	242.93	7	TRENT	47.99	43	DLF	11.5	79
BAJFINANCE	242.47	8	HINDALCO	47.95	44	PNB	10.66	80
SHRIRAMFIN	204.54	9	HINDUNILVR	43.98	45	DABUR	10.6	81
HEROMOTOCO	204.13	10	BPCL	43.92	46	BERGEPAINT	10.01	82
INDIGO	202.27	11	CHOLAFIN	43.74	47	ADANIGREEN	7.73	83
LTIM	154.18	12	SUNPHARMA	43.3	48	HDFCLIFE	7.61	84
EICHERMOT	152.8	13	ICICIGI	42.82	49	VBL	7.46	85
TCS	129.2	14	ADANIPORTS	42.17	50	ATGL	6.27	86
INDUSINDBK	115.41	15	ZYDUSLIFE	41.57	51	ICICIPRULI	6.03	87
RELIANCE	101.61	16	SRF	41.45	52	IRFC	4.93	88
TATAMOTORS	101.59	17	ADANIPOWER	41.44	53	MOTHERSON	4.59	89
LT	97.13	18	DMART	40.74	54	ADANIENSOL	1.24	90
BRITANNIA	90.83	19	TITAN	38.91	55	ZOMATO	0.69	91
HDFCBANK	89.75	20	BANKBARODA	36.82	56	TATASTEEL	-3.39	92
M&M	88.8	21	TVSMOTOR	36.06	57	GODREJCP	-4.19	93
AXISBANK	86.63	22	PIDILITIND	35.95	58			
GRASIM	78.5	23	ONGC	35.37	59			
SBIN	76.05	24	ADANIENT	35.27	60			
ABB	75.71	25	NESTLEIND	33.65	61			
APOLLOHOSP	72.14	26	JSWSTEEL	29.93	62			
SIEMENS	68.08	27	TECHM	25.77	63			
LICI	66.13	28	SBICARD	25.36	64			
ICICIBANK	64.56	29	HAVELLS	22.2	65			
INFY	64.21	30	NTPC	22.08	66			
DIVISLAB	63.06	31	IOC	21.83	67			
PFC	62.81	32	WIPRO	21.39	68			
HCLTECH	60.53	33	SBILIFE	20.29	69			
COALINDIA	59.34	34	BHARTIARTL	17.7	70			
RECLTD	55.59	35	CANBK	17.21	71			
JINDALSTEL	54.82	36	GAIL	17.17	72			

Journal of Informatics Education and Research
ISSN: 1526-4726
Vol 4 Issue 3 (2024)

1.2. Size Factor: Portfolio - 2

Company Name	Market Capitalization Value (in Cr)	Rank	Company Name	Market Capitalization Value (in Cr)	Rank	Company Name	Market Capitalization Value (in Cr)	Rank
ATGL	55.47	1	LICI	273.94	38	NTPC	868.41	75
BAJAJHLDNG	59.91	2	TATACONSUM	280.05	39	AXISBANK	925.93	76
SHREECEM	64.74	3	APOLLOHOSP	290.26	40	TATAPOWER	950.99	77
ADANIENSOL	66.78	4	INDIGO	294.32	41	LT	1,036.07	78
GODREJCP	76.76	5	DIVISLAB	296.77	42	MOTHERSON	1,084.56	79
ADANIPOWER	85.17	6	ADANIPORTS	302.22	43	ZOMATO	1,102.33	80
ICICIGI	86.78	7	GRASIM	302.78	44	BAJFINANCE	1,285.14	81
TORNTPHARM	88.51	8	WIPRO	308.35	45	BHARTIARTL	1,309.60	82
SBICARD	93.7	9	ASIANPAINT	310.12	46	TRENT	1,342.83	83
ICICIPRULI	96.03	10	NESTLEIND	317.49	47	TATASTEEL	1,454.14	84
BERGEPAINT	110.19	11	BPCL	324.49	48	ICICIBANK	1,472.66	85
AMBUJACEM	119.92	12	RECLTD	325.79	49	M&M	1,488.65	86
IRCTC	123.04	13	LTIM	329.88	50	TCS	1,699.98	87
BOSCHLTD	140.27	14	ULTRACEMCO	330.93	51	INFY	1,703.66	88
PIDILITIND	146.73	15	COALINDIA	346.67	52	SBIN	1,848.76	89
COLPAL	157.71	16	TECHM	349.09	53	MARUTI	1,947.56	90
DABUR	161.26	17	CANBK	360.83	54	TATAMOTORS	2,130.05	91
ADANIGREEN	165.73	18	PNB	369.94	55	RELIANCE	2,817.98	92
NAUKRI	167.85	19	DRREDDY	382.15	56	HDFCBANK	2,836.69	93
CHOLAFIN	173.21	20	SHRIRAMFIN	384.63	57			
BANKBARODA	180.26	21	DLF	392.07	58			
ABB	186.65	22	EICHERMOT	392.23	59			
IOC	193.33	23	PFC	412.63	60			
DMART	193.86	24	CIPLA	423.65	61			
SIEMENS	194.26	25	SUNPHARMA	462.93	62			
JINDALSTEL	195.31	26	ADANIENT	482.57	63			
ZYDUSLIFE	198.07	27	INDUSINDBK	490.07	64			
HDFCLIFE	203.2	28	BAJAJFINSV	499.36	65			
BRITANNIA	203.55	29	HINDUNILVR	564.09	66			
TVSMOTOR	205.8	30	GAIL	586.41	67			
VBL	206.96	31	POWERGRID	678.6	68			
MARICO	237.2	32	TITAN	696.03	69			
SRF	244.04	33	HEROMOTOCO	752.59	70			
HAVELLS	247.91	34	HCLTECH	770.45	71			
SBILIFE	264.11	35	HINDALCO	771.55	72			
IRFC	266.43	36	BAJAJ-AUTO	806.64	73			
JSWSTEEL	270.28	37	ONGC	818.77	74			

Journal of Informatics Education and Research
ISSN: 1526-4726
Vol 4 Issue 3 (2024)

1.3. Value Factor: Portfolio - 3

Company Name	Average % change	Rank	Company Name	Average % change	Rank	Company Name	Average % change	Rank
ADANIGREEN	9.16%	1	BAJAJHLDNG	2.10%	38	BOSCHLTD	1.20%	75
ADANIPOWER	6.83%	2	ZOMATO	2.09%	39	LICI	1.17%	76
ADANIENT	6.45%	3	TITAN	2.07%	40	GODREJCP	1.17%	77
IRFC	6.15%	4	INDIGO	2.05%	41	COALINDIA	1.08%	78
ATGL	6.07%	5	DMART	2.05%	42	EICHERMOT	1.07%	79
ADANIENSOL	4.63%	6	BAJAJ-AUTO	2.00%	43	SHREECEM	1.05%	80
TRENT	4.35%	7	CANBK	1.93%	44	BPCL	1.05%	81
VBL	4.34%	8	PIDILITIND	1.90%	45	ONGC	1.04%	82
IRCTC	4.01%	9	AMBUJACEM	1.86%	46	HDFCBANK	1.02%	83
PFC	3.21%	10	SUNPHARMA	1.84%	47	HEROMOTOCO	1.01%	84
JINDALSTEL	3.20%	11	HCLTECH	1.82%	48	HINDUNILVR	1.01%	85
ABB	3.16%	12	SHRIRAMFIN	1.81%	49	MARICO	1.00%	86
SRF	2.98%	13	BANKBARODA	1.80%	50	INDUSINDBK	0.99%	87
APOLLOHOSP	2.97%	14	DRREDDY	1.77%	51	DABUR	0.98%	88
CHOLAFIN	2.96%	15	ULTRACEMCO	1.75%	52	ICICIPRULI	0.95%	89
SIEMENS	2.96%	16	AXISBANK	1.75%	53	IOC	0.80%	90
TATAPOWER	2.93%	17	ZYDUSLIFE	1.76%	54	MARUTI	0.76%	91
RECLTD	2.91%	18	NESTLEIND	1.70%	55	SBICARD	0.71%	92
NAUKRI	2.85%	19	POWERGRID	1.69%	56	HDFCLIFE	0.66%	93
BAJFINANCE	2.74%	20	LT	1.68%	57			
TATAMOTORS	2.70%	21	INFY	1.65%	58			
DLF	2.58%	22	CIPLA	1.64%	59			
ADANIPORTS	2.42%	23	NTPC	1.63%	60			
M&M	2.38%	24	MOTHERSON	1.63%	61			
HINDALCO	2.37%	25	GRASIM	1.63%	62			
BAJAJFINSV	2.37%	26	TCS	1.61%	63			
LTIM	2.35%	27	ASIANPAINT	1.54%	64			
ICICIBANK	2.33%	28	TECHM	1.53%	65			
TORNTPHARM	2.25%	29	COLPAL	1.52%	66			
TATACONSUM	2.25%	30	WIPRO	1.52%	67			
DIVISLAB	2.25%	31	SBIN	1.45%	68			
JSWSTEEL	2.23%	32	BERGEPAINT	1.43%	69			
TVSMOTOR	2.19%	33	SBILIFE	1.37%	70			
HAVELLS	2.18%	34	GAIL	1.34%	71			
RELIANCE	2.17%	35	ICICIGI	1.32%	72			
TATASTEEL	2.13%	36	BRITANNIA	1.28%	73			
BHARTIARTL	2.12%	37	PNB	1.22%	74			

Journal of Informatics Education and Research
ISSN: 1526-4726
Vol 4 Issue 3 (2024)

Annexure 2: Equal Weighting Strategy

2.1. Portfolio - 1 (based on Value factor)

Value Factor					
Company Name	**Rank**	**Returns**	**Weights**	**Weighted RETURN**	**diff^2**
BOSCHLTD	1	0.97	0.10	0.0966	0.7559
BAJAJHLDNG	2	0.49	0.10	0.0494	0.1977
SHREECEM	3	0.02	0.10	0.0024	0.0005
MARUTI	4	0.28	0.10	0.0277	0.0622
DRREDDY	5	0.24	0.10	0.0243	0.0478
BAJAJ-AUTO	6	1.53	0.10	0.1530	1.8961
ULTRACEMCO	7	0.47	0.10	0.0466	0.1759
BAJFINANCE	8	0.00	0.10	0.0002	0.0000
SHRIRAMFIN	9	0.94	0.10	0.0935	0.7081
HEROMOTOCO	10	1.01	0.10	0.1010	0.8263
		SUM	1.00	0.5947	
		Stdev	0.0498		
		Sortino Ratio	0.62386		

2.2. Portfolio - 2 (based on Size factor)

Size Factor					
Company Name	**Ranking**	**Returns**	**Weights**	**Weighted RETURN**	**diff^2**
ATGL	1	0.26	0.10	0.0260	0.0548
BAJAJHLDNG	2	0.49	0.10	0.0494	0.1977
SHREECEM	3	0.02	0.10	0.0024	0.0005
ADANIENSOL	4	0.22	0.10	0.0216	0.0378
GODREJCP	5	0.40	0.10	0.0402	0.1309
ADANIPOWER	6	0.74	0.10	0.0743	0.4472
ICICIGI	7	0.76	0.10	0.0756	0.4629
TORNTPHARM	8	0.87	0.10	0.0869	0.6117
SBICARD	9	0.01	0.10	0.0005	0.0000
ICICIPRULI	10	0.40	0.10	0.0395	0.1264
		SUM	1.00	0.4164	
		Stdev	0.030		
		Sortino Ratio	0.4153		

2.3. Portfolio - 3 (based on Momentum factor)

Momentum Factor					
Company Name	**Rank (Momentum)**	**Returns**	**Weights**	**Weighted RETURN**	**diff^2**
ADANIGREEN	1	0.96	0.10	0.0958	0.7434

ADANIPOWER	2	0.74	0.10	0.0743	0.4472
ADANIENT	3	0.27	0.10	0.0265	0.0569
IRFC	4	1.10	0.10	0.1100	0.9801
ATGL	5	0.26	0.10	0.0260	0.0548
ADANIENSOL	6	0.22	0.10	0.0216	0.0378
TRENT	7	2.79	0.10	0.2790	6.3051
VBL	8	0.61	0.10	0.0608	0.2994
IRCTC	9	0.38	0.10	0.0376	0.1145
PFC	10	1.02	0.10	0.1020	0.8427
		SUM	1.00	0.8336	
		Stdev	0.0764		
		Sortino Ratio	0.9075		

Annexure 3: Mix Weighting Strategy

3.1. Portfolio - 4 (based on Value, Size & Momentum factor)

	Company Name	Rank	Returns	Weights	Weighted Return	diff^2
VALUE	BOSCHLTD	1	0.97	0.033	0.0322	0.872
	BAJAJHLDNG	2	0.49	0.033	0.0165	0.228
	SHREECEM	3	0.02	0.033	0.0008	0.0005
	MARUTI	4	0.28	0.033	0.0092	0.0717
	DRREDDY	5	0.24	0.033	0.0081	0.0552
	BAJAJ-AUTO	6	1.53	0.033	0.051	2.1874
	ULTRACEMCO	7	0.47	0.033	0.0155	0.2029
	BAJFINANCE	8	0	0.033	0.0001	0
	SHRIRAMFIN	9	0.94	0.033	0.0312	0.8169
	HEROMOTOCO	10	1.01	0.033	0.0337	0.9532
SIZE	ATGL	1	0.26	0.033	0.0087	0.0632
	BAJAJHLDNG	2	0.49	0.033	0.0165	0.228
	SHREECEM	3	0.02	0.033	0.0008	0.0005
	ADANIENSOL	4	0.22	0.033	0.0072	0.0436
	GODREJCP	5	0.4	0.033	0.0134	0.151
	ADANIPOWER	6	0.74	0.033	0.0248	0.5159
	ICICIGI	7	0.76	0.033	0.0252	0.5341
	TORNTPHARM	8	0.87	0.033	0.029	0.7057
	SBICARD	9	0.01	0.033	0.0002	0
	ICICIPRULI	10	0.4	0.033	0.0132	0.1458
MOMENTUM	ADANIGREEN	1	0.96	0.033	0.0319	0.8576
	ADANIPOWER	2	0.74	0.033	0.0248	0.5159
	ADANIENT	3	0.27	0.033	0.0088	0.0656
	IRFC	4	1.1	0.033	0.0367	1.1307
	ATGL	5	0.26	0.033	0.0087	0.0632
	ADANIENSOL	6	0.22	0.033	0.0072	0.0436
	TRENT	7	2.79	0.033	0.093	7.2738
	VBL	8	0.61	0.033	0.0203	0.3454
	IRCTC	9	0.38	0.033	0.0125	0.1321
	PFC	10	1.02	0.033	0.034	0.9722
				SUM	0.6149	
				STDEV	0.0188	
				Sortino Ratio	1.26	

Journal of Informatics Education and Research
ISSN: 1526-4726
Vol 4 Issue 3 (2024)

Annexure 4: Integrated Weighting Strategy

4.1. Portfolio - 5 (based on Value & Momentum factor)

Company Name	Rank (Value)	Rank (Momentum)	Average Integrated Ranks (VM)	Returns	Weights	Weighted Returns	diff^2
BAJFINANCE	8	20	14	0	0.1	0.0002	0.000004
ABB	25	12	18.5	0.98	0.1	0.0983	0.7827
TATAMOTORS	17	21	19	0.62	0.1	0.0617	0.3084
LTIM	12	27	19.5	0.17	0.1	0.0166	0.0223
APOLLOHOSP	26	14	20	0.44	0.1	0.0441	0.1575
BAJAJHLDNG	2	38	20	0.49	0.1	0.0494	0.1977
PFC	32	10	21	1.02	0.1	0.102	0.8427
SIEMENS	27	16	21.5	1.01	0.1	0.101	0.8263
M&M	21	24	22.5	1.05	0.1	0.105	0.893
JINDALSTEL	36	11	23.5	0.51	0.1	0.0508	0.209
BAJAJ-AUTO	6	43	24.5	0.63	=Avg		
TRENT	43	7	25		Stdev	0.0377	
RELIANCE	16	35	25.5		Sortino	0.5944	
INDIGO	11	41	26				
RECLTD	35	18	26.5				
ADANIPOWER	53	2	27.5				
DRREDDY	5	51	28				
ICICIBANK	29	28	28.5				
SHRIRAMFIN	9	49	29				
ULTRACEMCO	7	52	29.5				
NAUKRI	42	19	30.5				
CHOLAFIN	47	15	31				
DIVISLAB	31	31	31				
ADANIENT	60	3	31.5				
BAJAJFINSV	39	26	32.5				
SRF	52	13	32.5				
HINDALCO	44	25	34.5				
TORNTPHARM	41	29	35				
ADANIPORTS	50	23	36.5				
AXISBANK	22	53	37.5				
LT	18	57	37.5				
BOSCHLTD	1	75	38				

Journal of Informatics Education and Research
ISSN: 1526-4726
Vol 4 Issue 3 (2024)

4.2. Portfolio - 6 (based on Size & Momentum factor)

Company Name	Rank (Size)	Rank (Momentum)	Average Integrated Ranks (SM)	Returns	Weights	Weighted Returns	diff^2
ATGL	1	5	3	0.26	0.1	0.026	0.0548
ADANIPOWER	6	2	4	0.74	0.1	0.0743	0.4472
ADANIENSOL	4	6	5	0.22	0.1	0.0216	0.0378
ADANIGREEN	18	1	9.5	0.96	0.1	0.0958	0.7434
IRCTC	13	9	11	0.38	0.1	0.0376	0.1145
ABB	22	12	17	0.98	0.1	0.0983	0.7827
CHOLAFIN	20	15	17.5	0.32	0.1	0.0319	0.0824
JINDALSTEL	26	11	18.5	0.51	0.1	0.0508	0.209
TORNTPHARM	8	29	18.5	0.87	0.1	0.0869	0.6117
NAUKRI	19	19	19	0.96	0.1	0.0956	0.7403
VBL	31	8	19.5	0.62	=Avg		
BAJAJHLDNG	2	38	20		Stdev	0.0315	
IRFC	36	4	20		Sortino	0.5645	
SIEMENS	25	16	20.5				
SRF	33	13	23				
APOLLOHOSP	40	14	27				
AMBUJACEM	12	46	29				
PIDILITIND	15	45	30				
TVSMOTOR	30	33	31.5				
ADANIENT	63	3	33				
ADANIPORTS	43	23	33				
DMART	24	42	33				
RECLTD	49	18	33.5				
HAVELLS	34	34	34				
JSWSTEEL	37	32	34.5				
TATACONSUM	39	30	34.5				
PFC	60	10	35				
BANKBARODA	21	50	35.5				
DIVISLAB	42	31	36.5				
LTIM	50	27	38.5				
ICICIGI	7	72	39.5				
BERGEPAINT	11	69	40				
DLF	58	22	40				
ZYDUSLIFE	27	54	40.5				
COLPAL	16	66	41				
GODREJCP	5	77	41				
INDIGO	41	41	41				
SHREECEM	3	80	41.5				
BOSCHLTD	14	75	44.5				
TRENT	83	7	45				
BAJAJFINSV	65	26	45.5				
TATAPOWER	77	17	47				
HINDALCO	72	25	48.5				
CANBK	54	44	49				
ICICIPRULI	10	89	49.5				
BAJFINANCE	81	20	50.5				
SBICARD	9	92	50.5				
BRITANNIA	29	73	51				
NESTLEIND	47	55	51				

4.3. Portfolio - 7 (based on Size & Value factor)

Company Name	Rank (Size)	Rank (Value)	Average Integrated Ranks (SV)	Returns	Weights	Weighted Returns	diff^2
BAJAJHLDNG	2	2	2	0.49	0.1	0.0494	0.1977
SHREECEM	3	3	3	0.02	0.1	0.0024	0.0005
BOSCHLTD	14	1	7.5	0.97	0.1	0.0966	0.7559
ABB	22	25	23.5	0.98	0.1	0.0983	0.7827
BRITANNIA	29	19	24	0.39	0.1	0.0386	0.1207
TORNTPHARM	8	41	24.5	0.87	0.1	0.0869	0.6117
INDIGO	41	11	26	1.11	0.1	0.111	0.998
SIEMENS	25	27	26	1.01	0.1	0.101	0.8263
COLPAL	16	40	28	0.9	0.1	0.0902	0.659
ICICIGI	7	49	28	0.76	0.1	0.0756	0.4629
ULTRACEMCO	51	7	29	0.75	=Avg		
ADANIPOWER	6	53	29.5		Stdev	0.0343	
DRREDDY	56	5	30.5		Sortino	0.6718	
NAUKRI	19	42	30.5				
JINDALSTEL	26	36	31				
LTIM	50	12	31				
APOLLOHOSP	40	26	33				
LICI	38	28	33				
SHRIRAMFIN	57	9	33				
CHOLAFIN	20	47	33.5				
GRASIM	44	23	33.5				
EICHERMOT	59	13	36				
DIVISLAB	42	31	36.5				
PIDILITIND	15	58	36.5				
SBICARD	9	64	36.5				
BANKBARODA	21	56	38.5				
DMART	24	54	39				
ZYDUSLIFE	27	51	39				
BAJAJ-AUTO	73	6	39.5				
INDUSINDBK	64	15	39.5				
HEROMOTOCO	70	10	40				
ASIANPAINT	46	38	42				
RECLTD	49	35	42				
SRF	33	52	42.5				
AMBUJACEM	12	74	43				
COALINDIA	52	34	43				
ATGL	1	86	43.5				
TVSMOTOR	30	57	43.5				
IRCTC	13	75	44				
BAJFINANCE	81	8	44.5				
IOC	23	67	45				
PFC	60	32	46				
ADANIPORTS	43	50	46.5				
BERGEPAINT	11	82	46.5				
ADANIENSOL	4	90	47				
BPCL	48	46	47				
MARUTI	90	4	47				
LT	78	18	48				
ICICIPRULI	10	87	48.5				

Annexure 5: Sequential Weighting Strategy

5.1. Portfolio - 8 (based on factors from a Speculative viewpoint)

Company Name (Small Cap)	Ranking (SIZE)	Company Name	Rank (Momentum)	Company Name	Rank (Value)	Returns	Weights	Weighted Returns	diff^2
ATGL	1	HDFCLIFE	93	GODREJCP	93	0.4	0.1	0.0402	0.1309
BAJAJHLDNG	2	SBICARD	92	ICICIPRULI	87	0.4	0.1	0.0395	0.1264
SHREECEM	3	IOC	90	HDFCLIFE	84	0.15	0.1	0.015	0.0182
ADANIENSOL	4	ICICIPRULI	89	BERGEPAINT	82	0.08	0.1	0.0084	0.0058
GODREJCP	5	DABUR	88	DABUR	81	0.16	0.1	0.0157	0.02
ADANIPOWER	6	MARICO	86	MARICO	76	0.24	0.1	0.0237	0.0455
ICICIGI	7	SHREECEM	80	AMBUJACEM	74	0.51	0.1	0.051	0.2107
TORNTPHARM	8	GODREJCP	77	SBILIFE	69	0.46	0.1	0.046	0.1714
SBICARD	9	LICI	76	WIPRO	68	0.34	0.1	0.0337	0.092
ICICIPRULI	10	BOSCHLTD	75	IOC	67	1	0.1	0.1	0.81
BERGEPAINT	11	BRITANNIA	73	SBICARD	64		STDEV=	0.0263	0.3686
AMBUJACEM	12	ICICIGI	72	NESTLEIND	61		Average Returns	0.0373	
IRCTC	13	SBILIFE	70	PIDILITIND	58				
BOSCHLTD	14	BERGEPAINT	69	BANKBARODA	56				
PIDILITIND	15	WIPRO	67	DMART	54				
COLPAL	16	COLPAL	66	ZYDUSLIFE	51				
DABUR	17	ASIANPAINT	64	ICICIGI	49				
ADANIGREEN	18	GRASIM	62	COLPAL	40				
NAUKRI	19	NESTLEIND	55	ASIANPAINT	38				
CHOLAFIN	20	ZYDUSLIFE	54	LICI	28				
BANKBARODA	21	BANKBARODA	50	GRASIM	23				
ABB	22	AMBUJACEM	46	BRITANNIA	19				
IOC	23	PIDILITIND	45	INDIGO	11				
DMART	24	DMART	42	SHREECEM	3				
SIEMENS	25	INDIGO	41	BOSCHLTD	1				
JINDALSTEL	26	BAJAJHLDNG	38						
ZYDUSLIFE	27	HAVELLS	34						
HDFCLIFE	28	TVSMOTOR	33						
BRITANNIA	29	JSWSTEEL	32						
TVSMOTOR	30	DIVISLAB	31						
VBL	31	TATACONSUM	30						
MARICO	32	TORNTPHARM	29						
SRF	33	ADANIPORTS	23						
HAVELLS	34	NAUKRI	19						
SBILIFE	35	SIEMENS	16						
IRFC	36	CHOLAFIN	15						
JSWSTEEL	37	APOLLOHOSP	14						
LICI	38	SRF	13						
TATACONSUM	39	ABB	12						
APOLLOHOSP	40	JINDALSTEL	11						
INDIGO	41	IRCTC	9						
DIVISLAB	42	VBL	8						
ADANIPORTS	43	ADANIENSOL	6						
GRASIM	44	ATGL	5						
WIPRO	45	IRFC	4						
ASIANPAINT	46	ADANIPOWER	2						
NESTLEIND	47	ADANIGREEN	1						

Journal of Informatics Education and Research
ISSN: 1526-4726
Vol 4 Issue 3 (2024)

5.2. Portfolio - 9 (based on factors from a Conservative viewpoint)

Company Name (Large Cap)	Ranking (Size)	Company Name	Rank (Momentum)	Company Name	Rank (Value)	Returns	Weights	Weighted Returns	diff^2
HDFCBANK	93	ADANIENT	3	DRREDDY	5	0.24	0.1	0.0243	0.0478
RELIANCE	92	TRENT	7	BAJAJ-AUTO	6	1.53	0.1	0.153	1.8961
TATAMOTORS	91	PFC	10	ULTRACEMCO	7	0.47	0.1	0.0466	0.1759
MARUTI	90	TATAPOWER	17	BAJFINANCE	8	0	0.1	0.0002	0
SBIN	89	RECLTD	18	SHRIRAMFIN	9	0.94	0.1	0.0935	0.7081
INFY	88	BAJFINANCE	20	LTIM	12	0.17	0.1	0.0166	0.0223
TCS	87	TATAMOTORS	21	RELIANCE	16	0.31	0.1	0.0308	0.0768
M&M	86	DLF	22	TATAMOTORS	17	0.62	0.1	0.0617	0.3084
ICICIBANK	85	M&M	24	M&M	21	1.05	0.1	0.105	0.893
TATASTEEL	84	HINDALCO	25	ICICIBANK	29	0.39	0.1	0.0386	0.1207
TRENT	83	BAJAJFINSV	26	PFC	32		STDEV=	0.0471	0.5951
BHARTIARTL	82	LTIM	27	HCLTECH	33		Average Returns	0.057	
BAJFINANCE	81	ICICIBANK	28	RECLTD	35				
ZOMATO	80	RELIANCE	35	BAJAJFINSV	39				
MOTHERSON	79	TATASTEEL	36	TRENT	43				
LT	78	BHARTIARTL	37	HINDALCO	44				
TATAPOWER	77	ZOMATO	39	SUNPHARMA	48				
AXISBANK	76	TITAN	40	TITAN	55				
NTPC	75	BAJAJ-AUTO	43	ADANIENT	60				
ONGC	74	CANBK	44	BHARTIARTL	70				
BAJAJ-AUTO	73	SUNPHARMA	47	CANBK	71				
HINDALCO	72	HCLTECH	48	TATAPOWER	77				
HCLTECH	71	SHRIRAMFIN	49	DLF	79				
HEROMOTOCO	70	DRREDDY	51	ZOMATO	91				
TITAN	69	ULTRACEMCO	52	TATASTEEL	92				
POWERGRID	68	AXISBANK	53						
GAIL	67	POWERGRID	56						
HINDUNILVR	66	LT	57						
BAJAJFINSV	65	INFY	58						
INDUSINDBK	64	CIPLA	59						
ADANIENT	63	NTPC	60						
SUNPHARMA	62	MOTHERSON	61						
CIPLA	61	TCS	63						
PFC	60	TECHM	65						
EICHERMOT	59	SBIN	68						
DLF	58	GAIL	71						
SHRIRAMFIN	57	PNB	74						
DRREDDY	56	COALINDIA	78						
PNB	55	EICHERMOT	79						
CANBK	54	BPCL	81						
TECHM	53	ONGC	82						
COALINDIA	52	HDFCBANK	83						
ULTRACEMCO	51	HEROMOTOCO	84						
LTIM	50	HINDUNILVR	85						
RECLTD	49	INDUSINDBK	87						
BPCL	48	MARUTI	91						

Annexure 6: Linear Regression

(Regressing Returns on EPS, Market Capitalisation, Average Percentage Change in Price)

6.1. Regression and Computing R square

Model	R	R^2	Adjusted R^2	RMSE
1	0.22062	0.04868	0.01661	0.41393

Predictor	Estimate	SE	Lower	Upper	t	p
Intercept	0.40133	0.1037	0.19528	0.60738	3.87012	0.00021
EPS	0.00005	0.00032	-0.0006	0.00069	0.14392	0.88589
Mkt Cap	0.00005	0.00008	-0.0001	0.0002	0.61669	0.53901
Avg % change	6.67151	3.19156	0.32995	13.01308	2.09036	0.03944

6.2. Regressing Returns on EPS

Model	R	R^2	Adjusted R^2	RMSE
1	0.022	0.00048	-0.0105	0.42428

Predictor	Estimate	SE	Lower	Upper	t	p
Intercept	0.58444	0.05226	0.48063	0.68825	11.18304	< .00001
EPS	-0.00007	0.00032	-0.00071	0.00057	-0.20992	0.8342

6.3. Regressing Returns on Market Capitalisation

Model	R	R^2	Adjusted R^2	RMSE
1	0.03743	0.0014	-0.00957	0.42409

Predictor	Estimate	SE	Lower	Upper	t	p
Intercept	0.5636	0.0613	0.44184	0.68536	9.19419	< .00001
Mkt Cap	0.00003	0.00008	-0.00012	0.00018	0.3573	0.7217

6.4. Regressing Returns on Average Percentage Change in Price

Model	R	R^2	Adjusted R^2	RMSE
1	0.21056	0.04434	0.03383	0.41487

Predictor	Estimate	SE	Lower	Upper	t	p
Intercept	0.43836	0.08096	0.27754	0.59918	5.41437	< .00001
Avg % change	6.34718	3.08909	0.21107	12.48329	2.05471	0.04277