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SMART BETA INVESTING:

THE CORNERSTONE OF SYSTEMATIC ACTIVE INVESTING

Edited by: Mayank Joshipura

SVKM's Narsee Monjee Institute of Management Studies (NMIMS) Deemed-to-be-University

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Preface

Global Asset Under Management (AUM) has crossed the $100 trillion mark, higher than the world's GDP for 2023. Global asset managers include sovereign wealth funds, endowment funds, pension funds, mutual funds, hedge funds, and insurance companies, to name a few. Such firms invest in various financial, real, and digital assets. Equity is one of the most significant asset classes; hence, asset pricing and understanding cross-section differences in equity returns have long been an area of interest for academics and practitioners. This book offers insights into smart beta investment strategies that exploit factor premiums by constructing equity portfolios with smart beta tilt.

The first chapter offers an introduction to factor and smart beta investing by describing the evolution of asset pricing models, starting from the Capital Asset Pricing Model (CAPM) in the 1960s to multi-factor asset pricing models developed over time. It further explains systematic factors that explain the differences in cross-section equity returns and their possible systematic risk-based and behavioral explanations. Toward the end, it discusses how factor investing can combine the benefits of both discretionary active fund management and passive indexing/

The second chapter focuses on one of the oldest factors: size, where the portfolio comprising small market cap stocks outperforms the portfolio comprising their large counterparts. The chapter focuses on evidence and explanations of size premium, explanations for persistent small size effect, and potential risks associated with it, and delves into available products and theory performance that might help investors in exploiting the size effect in a smart beta way.

The third chapter narrates quality investing and the evolution of the value investment philosophy from investing in cheap stocks to looking for quality at a reasonable price. It describes various approaches to quality investing and the performance of smart beta indices tracking quality factors over time.

The fourth chapter describes momentum investing. The success of momentum investing challenged the foundation of the efficient market hypothesis and the debate on whether the superior performance of momentum investment strategy is attributable to systematic risk or behavioral errors committed by market participants. The chapters review evidence and explanations of the momentum effect.

The fifth chapter discusses the low volatility investing. Low-risk anomaly emerged as one of the biggest challenges to efficient market theory. There are alternative economic and behavioral explanations that try to explain (or explain away) such anomalous risk-return relationships. Multiple indices, index funds, and ETFs are launched to exploit the benefits of low-volatility investing. The chapters list some popular investment vehicles and discuss the performance of such investment strategies in the US and Indian markets.

The sixth chapter is about ESG investing. Environment, Social, and Governance have taken center stage in invitational investing, and firms and investment vehicles with favorable ESG characteristics have received significant inflows over the past decade. Whether ESG investing delivers superior returns and the explanations for the same, it discusses the available investment products tracking ESG investment strategies and their performance and the role of ESG as a factor in asset pricing.

The seventh chapter focuses on multi-factor investing and compares various approaches to combining multiple-factor exposures into one investment strategy. Mix, integrate, and sequential screening are three alternative approaches to implementing multi-factor investment strategies with their relative pros and cons. The chapter compares them with ways to design and implement such strategies.

Chapters eight and nine focus on the role of machine learning in the design and implementation of beta investment strategies, possible approaches, currently used cases, and future potential that can enhance the efficacy and performance of such investment strategies.

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Chapter-1

INTRODUCTION TO FACTOR AND SMART BETA INVESTING

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Abstract

Global mutual fund assets are expected to cross the $100 trillion mark by 2027. There has been a systematic outflow from active funds and an inflow toward passive funds. However, not all passive funds are conventional market cap or equal-weight market index trackers. A large chunk of flows into passive funds tracking active indices created and managed based on smart beta or factor investment strategies that combine the benefits of active investing in the potential for delivering alpha while maintaining the transparency and low cost of passive market indexers. This book dives deep into the evolution of smart beta or factor investment strategies, evidence and explanations of their superior performance, and opportunities and challenges in implementing and evaluating publicly traded long-only smart beta indices in global and Indian markets. It also explores the benefits of multiple smart beta investment strategies and the world of multifactor investing.

Introduction

What explains the difference in the cross-section of equity returns has remained a central question in finance. Many asset-pricing models, starting from single-factor linear asset pricing models such as the Capital Asset Pricing Model (CAPM) (Sharpe, 1964), offer ex-ante estimates of the required rate of returns on a stock based on market risk premium, prevailing risk-free rate, and beta of the security, which measures the systematic risk. Early tests of such models show that the ex-post returns of stocks are different from expected, and such differences are not random but systematic. Initially, such deviations were discarded as anomalies or data snooping exercises. However, strong evidence for value (Basu, 1977) and size (Banz, 1981) anomalies in the late 1970s and early 1980s and the persistence of such anomalies raised questions about the power of CAPM in explaining the cross-section differences in stock returns.

For example, value investing was pioneered by Benjamin Graham and established as a solid investment philosophy by some of his disciples, most notably Warren Buffet, who had already established his reputation as a successful value investor by the 1970s. Value investing saw initial success in an era where markets were believed to be fully efficient, prices were always correct, and no free lunch was possible. It took time to prove that stocks with specific securities should systematically outperform their counterparts over long periods.

However, early evidence of systematic value investing (Basu, 1977) found that stocks with low price-to-earnings ratios tend to outperform those with high price-to-earning ratios. Further, Bondt and Thaler (1985) showed that stock markets overreact and that there is a reversal of fortunes in the long run, where the basket of stocks with the highest price erosion in the previous three years would outperform the basket of stocks with the highest price gain in the corresponding period over the next three-year period. Such a reversal is difficult to explain by CAPM or similar models.

Likewise, Banz (1981) showed that the basket of small-cap stocks systematically outperformed the basket of large-cap stocks. That was called a size anomaly, and the differences in beta could not explain such a pattern. Eugene Fama, the proponent of efficient market theory, denounced the utility of beta and, in a way, CAPM (Fama & French, 1992) by showing that beta has no explanatory power in explaining cross-section differences in stock returns after controlling for size.

By the 1990s, several anomalies emerged to challenge the CAPM and efficient market theory. However, around the same time, Fama and French came up with a three-factor version of the asset pricing model by adding value and size factors to the market factor of CAPM. This three-factor model could explain all anomalies except medium-term momentum (Fama & French, 1996). The three-factor model considers value and size as sources of systematic risk associated with vulnerability to business cycle shocks, financial distress, and the risk of extinction, which could not be captured by beta and hence CAPM. However, many others objected to the higher risk associated with value stocks than their growth counterparts; as in the three-factor model, the value manifests merely in cheapness in relative valuation. Meanwhile, for the followers of Benjamin Graham's value investing style, value stocks offer the highest margin of safety due to their inherent cheap valuation, not because of their higher riskiness but because of erroneous valuation by the market. Such a high margin of safety makes it a safe investment opportunity rather than a riskier investment.

There is a difference between anomalies and factors. Anomalies could be an exercise in data mining or may persist for some time before they eventually disappear when more market participants try to exploit them. If any stock characteristic explains the difference among the cross-section of equity returns beyond the market factor and continues to explain it over a long time, it could be considered a factor. The factor explains such differences based on systematic risks or systematic errors. There are only two reasons for which such patterns persist. Such factor premiums are attributable to systematic risks that cannot be measured or captured by conventional measures such as beta. For example, crash risk is often not captured by beta.

As discussed earlier, while the three-factor asset pricing model could explain most anomalies of that time, it could not explain momentum, and momentum was accepted as one of the four factors in the asset pricing model (Carhart, 1997). However, many anomalies, such as low risk and quality, have emerged. To explain the outperformance of low-risk and quality stocks over time, the three-factor Fama-French model was further expanded to a five-factor asset pricing model with profitability and investment intensity were added to market, value, and size factors, which could explain risk and quality anomalies to some extent but not convincingly (Fama & French, 2015). However, given the lack of consensus around the five-factor model, new factors are proposed in the research, such as Betting Against Beta (BAB) (Frazzini & Pedersen, 2014) and Quality minus Junk (QMJ) (Asness et al., 2019).

Alternative Explanations to Factor Premiums

Systematic risk cannot be diversified away, and hence, an investor owning a basket of stocks is exposed to such risk. Such investors might expect and earn superior returns for bearing such risk. On the other hand, systematic errors are behavioral errors where market participants collectively behave in a specific manner when faced with a specific situation. Such behavior results in significant underreaction or overreaction to the outcome of the events or news, resulting in significant dislocation of the prices from their normal equilibrium, sometimes resulting in the bubble and subsequent crashes. Such price dislocation tends to persist due to limits of arbitrage and offers opportunities to investors who can avoid such systematic behavioral errors and exploit them to their advantage. While there is debate on which factors are relevant and whether risk-based or behavioral explanations drive superior returns of such factor portfolios, the global asset management industry has launched active and passive investment products to exploit these factors. Index manufacturers launched a set of factor indices that became vital benchmarks for actively managed investment portfolios aiming to exploit one or multiple factor premiums.

While most factors are constructed as market-neutral long-short portfolios, asset management firms and index providers offer implementable variants of such factor investment strategies and indices. While hedge funds continue to follow long-short factor investment strategies, asset managers such as pension funds and mutual funds facing long-only constraints tried to exploit the factor returns by tilting their portfolios toward the stocks with desired characteristics to earn a premium. The long-only indices and investment strategies focus only on the long leg of factor strategies, which became popular as smart beta investment strategies, smart beta indices, or active beta indices.

In addition, market, size, value, momentum, low volatility, quality, profitability, and investment intensity have emerged as important factors from the asset management industry perspective. Below is a brief description of each factor.

Size: Controlling for value exposure, the basket of small stocks outperforms that of large stocks.

Value: Controlling for size exposure, the basket of value stocks outperforms the basket of growth stocks, where the stocks are categorized in value and growth based on their relative valuation multiples.

Momentum: Controlling for size exposure, the basket of recent high-price momentum stocks outperforms the basket of low-price momentum stocks.

Investment: Controlling for other factors, stocks of firms with low investment intensity outperform stocks of firms with high investment intensity

Profitability: Controlling for other factors, stocks with high profitability outperform stocks with low profitability.

Betting against Beta (BAB): Controlling for other factors, the stocks with lower beta outperform stocks with high beta.

Quality minus Junk: Controlling for other factors, the high-quality stocks outperform low-quality stocks.

Stocks with low beta or risk, high profitability, and low investment intensity must represent a quality universe. Therefore, the quality factor is a combination of these three factors.

Table 1 shows the important factors and their possible systematic risk and systematic error-based explanations. It is worth noting that while size, value, dividend yield, and momentum factors have both risk-based and behavioral explanations, quality and low-volatility factors have no risk-based explanations as it is counterintuitive and difficult to justify that these portfolios' superior return is due to their higher riskiness.

Table 1: Popular systematic factors, risk-based, and behavioral theory-based explanations.

Systematic Factors	**Systematic risk-based theories**	**Behavioral theories**
Value	Higher systematic (business cycle) risk	Errors-in-expectations Loss aversion Investment-flows-based theory
Low Size (Small Cap)	Higher systematic (business cycle) risk Proxy for other types of systematic risk	Errors-in-expectations
Momentum	Higher systematic (business cycle) risk Higher systematic tail risk	Underreaction and overreaction Investment-flows-based theory
Low Volatility	N/A	Lottery effect Overconfidence effect Leverage aversion
Dividend Yield	Higher systematic (business cycle) risk	Errors-in-expectations
Quality	N/A	Errors-in-expectations

Table 2 shows possible metrics used to construct and operationalize smart beta long-only investment strategies and indices. One must note that multiple choice metrics exist to construct portfolios to track any given factors. In addition, one has to decide the portfolio weighing scheme and rebalancing frequency. So, while factor investment strategies are rule-based systematic investment strategies, they still require many active choices in designing, constructing, and implementing such investment strategies.

Table 2: Popular factors, description, and metrics used for portfolio construction

Systematic Factors	**Description**	**Metrics**
Value	captures excess returns to stocks that have low prices relative to their fundamental value	Book to price, earnings to price, book value, sales, earnings, cash earnings, net profit, dividends, cash flow
Low Size (Small Cap)	Captures excess returns of smaller firms (by market capitalization) relative to their larger counterparts	Market capitalization (full or free float
Momentum	Reflects excess returns to stocks with stronger past performance	Relative returns (3-mth, 6-mth, 12-mth, sometimes with the last 1 mth excluded), historical alpha
Low Volatility	Captures excess returns to stocks with lower-than-average volatility, beta, and/or idiosyncratic risk	Standard deviation (1-yr, 2-yrs, 3-yrs), Downside standard deviation, standard deviation of idiosyncratic returns, beta

Systematic Factors	**Description**	**Metrics**
Dividend Yield	Captures excess returns to stocks that have higher-than-average dividend yields	Dividend yield
Quality	Captures excess returns to stocks that are characterized by low debt, stable earnings growth, and other "quality" metrics	ROE, earnings stability, dividend growth stability, strength of balance sheet, financial leverage, accounting policies, strength of management, accruals, cash flows

Conclusion

To conclude, the factor investment strategies offer benefits of both active and passive investment strategies (Figure 1). While active strategies offer the potential to earn active returns (alpha) delivered through active investment portfolio management, they rely on discretionary implementation by the fund managers, hence lacking transparency and often having high asset management fees and implementation costs. On the other hand, passive market index tracker strategies enjoy the benefit of low cost and transparent implementation. However, one has to settle with market returns and forgo potential opportunities to earn active returns. Factor investment strategies or their smart beta avatars offer the benefits of active returns, low cost, and transparent implementation. No wonder the investment smart beta investment strategies have gained significant traction and popularity among institutional and individual investors over the last decade.

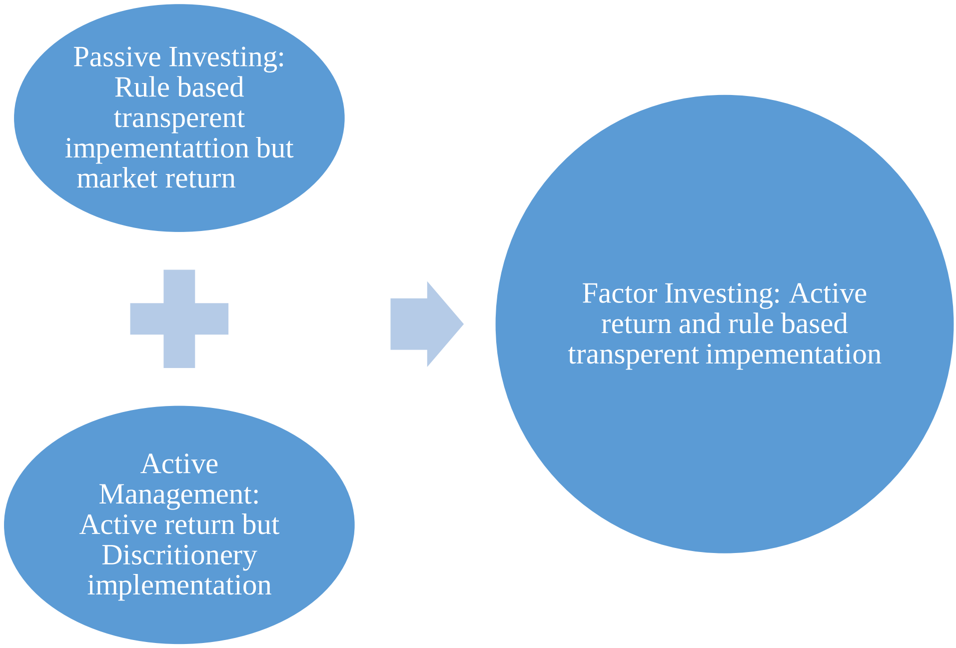

Figure 1: Factor investing: Combining the benefits of active and passive investing

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Chapter-2

SMALL CAP INVESTING

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Introduction

Investing in small companies is a dynamic and appealing approach that provides access to many investment opportunities, growth, and innovation. This chapter will delve into the fascinating world of small-cap stocks, covering the tactics, dangers, and opportunities that come with being a part of this particular sector of the financial markets.

Market capitalization, sometimes shortened to "market cap," is a crucial financial indicator showing the entire worth of an organization listed on a stock exchange. It is computed by multiplying the market value of the outstanding shares of a corporation by the total quantity of those shares. A key metric that sheds light on a company's size, importance in the financial markets, and relative valuation concerning other businesses is market capitalization.

Here is the formula to calculate market capitalization:

$$\text{Market Cap} = \text{Stock Price} \times \text{Total Outstanding Shares}$$

Usually, the most recent closing price of the stock is utilized in the computation, but depending on the situation, it may also be based on the current market price.

Size Categories: Businesses are categorized into various size groups based on market capitalization. Although these classifications may differ, they are commonly characterized as follows:

- Large-Cap: Large-cap corporations usually have the most significant market capitalizations on the stock exchange. Although the exact market capitalization criterion varies, it often hovers around INR 20,000 crores or above.

- Mid-Cap: Market capitalizations of mid-cap corporations are usually not as high as those of large-caps, but they are nonetheless significant. This range is commonly defined in India as between INR 5,000 and INR 20,000 crores.

- Small-cap: Small-cap companies have the smallest market capitalizations of the three categories. Small-cap firms in India frequently have market valuations of less than INR 5,000 crores.

Remembering that these cutoff points are flexible and subject to change in response to local norms and market conditions is crucial.

A key idea in the finance and investment industries is market capitalization. It gives analysts and investors essential details about a company's size, place in the market, and risk-return profile. To create well-diversified portfolios and make wise investing decisions, one must have a solid understanding of market capitalization. When choosing an investment, investors must consider market capitalization. Investors typically identify each group with different tactics and risk tolerances. Small-cap stocks are frequently perceived as riskier but with the potential for faster growth, whereas large-cap stocks are generally considered more stable and less hazardous (Arshanapalli and Nelson, 2007). Index construction and benchmarking both use market capitalization. Market capitalization is used by stock market indices, such as the S&P 500, NASDAQ, and Dow Jones Industrial Average, to choose and weight their participants. These indices can be used as performance benchmarks for investments since they show the performance of particular market segments. Higher market capitalization firms frequently have larger trading volumes, which can lead to better liquidity and smaller bid-ask gaps. Due to lower trading volumes, smaller companies with smaller market values could have less liquidity and more dramatic price movements. Market capitalization is employed when comparing the relative values of businesses in the same sector or industry. A company with a smaller market cap could be deemed cheap if its key performance indicators are comparable to a rival with a larger market capitalization. Smaller market caps are frequently linked to more significant growth potential by investors. If smaller businesses successfully gain market share or meet their growth goals, they might have more substantial space for expansion and be able to produce sizable profits (Bauman et al., 1998).

Criteria	**Large-Cap**	**Mid-Cap**	**Small-cap**
Market Capitalisation	Typically INR 20,000 crores or more	INR 5,000 crores to INR 20,000 crores (approx.)	Below INR 5,000 crores (approx.)
Revenue and Profitability	Significant revenue and profitability	Good revenue and profitability but may be lower	May have lower revenue and may not be profitable
Growth Potential	Generally stable and established companies	Moderate growth potential	High growth potential, often in the early stages
Liquidity and Trading Volume	High liquidity and trading volumes	Moderate liquidity and trading volumes	Lower liquidity and trading volumes
Inclusion in Major Indices	Included in major stock market indices (e.g.,	May or may not be included in major indices	Typically not included in major indices

	Nifty 50 or BSE Sensex)		
Market Representation	Represents a significant portion of the market	Represents a smaller portion of the market	Represents a tiny portion of the market
Investor Preference	Often preferred by conservative or income-oriented investors	Attractive to growth-oriented investors	Appealing to investors seeking high-risk, high-reward opportunities
Industry Dominance	Often industry leaders	May be competitive but not necessarily dominant	May be disruptors or niche players
Regulatory Compliance	Subject to extensive regulatory requirements	Subject to regulatory requirements but with some flexibility	Subject to regulatory requirements, often with fewer restrictions

Defining Small-cap Stocks: "small-cap stocks" means equities of businesses with comparatively small market capitalizations. Small-cap companies are defined differently but usually have market capitalizations of less than 5000 crores. These tiny businesses promise investors rapid development potential, but they also have the following distinctive qualities.

- **Growth Potential**: Small-cap stocks are frequently linked to growth's attractiveness. These businesses, which are often just getting started, have the potential to grow their sales and profits quickly. Small-cap stocks appeal to investors because they allow them to profit from the ascent of future market leaders.

- **Higher Risk and Volatility**: Small-cap stocks are characterized by elevated risk and volatility. Significant price swings affect smaller businesses in reaction to news about the company or changes in the market. Although this volatility may present possibilities, effective risk management is also necessary.

- **Market Capitalisation Matters**: In investing, a company's market capitalization indicates its size. The size of small-cap stocks is smaller than that of mid-cap and large-cap companies. Their market behavior, access to money, and growth paths are different.
- **Lower Liquidity**: In comparison to larger companies, small-cap stocks could have lower trading volumes and liquidity, which could lead to wider bid-ask spreads and, therefore, more significant transaction costs.
- **Less Institutional Coverage**: Institutional investors and analysts might pay less attention to smaller businesses than they do to larger, more extensively covered ones. This may present chances for investors to find ignored or cheap stocks.
- **Limited Analyst Coverage:** Wall Street analysts and institutional investors pay less attention to small-cap stocks. Due to market inefficiencies brought about by this lack of coverage, there may be possibilities for lone investors who are prepared to conduct independent studies and find hidden treasures.
- **Diversification:** Adding small-cap stocks to your investment portfolio might aid in investment diversification. By distributing risk among several asset classes, diversification may lower the total risk of a portfolio.
- **Potential for Early Discovery:** Purchasing small-cap stocks might help you find businesses that have the potential to be the next big thing. Consider the early investors in companies that have grown into titans, such as Amazon, Google, or Netflix, which were formerly small-cap stocks.

- **Entrepreneurial Spirit**: Many small-cap firms are started and run by highly driven and enthusiastic business owners. Small-cap companies are more robust and pioneering.

- **The Path Ahead**: A journey full of growth tales, entrepreneurial passion, and the possibility of significant financial returns is a small-cap investment.

Small-cap stocks appeal to investors because of their potential for growth and potential for more significant profits. However, it is crucial to understand that small-cap companies carry a higher risk because of their smaller size, possibility for reduced liquidity, and increased susceptibility to market volatility. They should, therefore, be carefully considered in light of an investor's investing goals, risk tolerance, and overall portfolio diversification strategy, as they may not be appropriate for all investors.

Risks of Small-cap Investing

While there is a chance for greater gains when investing in small-cap stocks, particular risks and difficulties are involved. Investors should be aware of these dangers before investing in small-cap enterprises. The following are some of the main dangers connected to small-cap investing:

- Volatility: Compared to large-cap equities, small-cap stocks are typically more volatile. Over brief intervals, their prices may fluctuate significantly, resulting in both big gains and losses.

- Lack of Liquidity: Because small-cap companies frequently have lower trading volumes and liquidity, it might be harder to acquire or sell shares without impacting the company's price. Wider bid-ask spreads and possible difficulties executing big trades may result from this.

- Limited Resources: Due to their potential lack of financial resources, small-cap businesses are more susceptible to pressure from competition and economic downturns. They can have trouble raising money as well.

- Market Risk: Small-cap equities are susceptible to macroeconomic and general market conditions. Bear markets and economic downturns may affect small-cap stocks more sharply.

- Financial Risk: Smaller businesses could be more susceptible to financial hardship because they have fewer resources. They can have trouble paying off debt and getting access to capital markets.

- Lack of Diversification: Smaller businesses tend to be less diversified than larger enterprises since they may only serve specific markets or sectors of the economy. Due to this lack of diversification, investors may be at risk from industry-specific issues.

- Information Asymmetry: Analysts and institutional investors may pay smaller businesses less attention than they do larger ones. As a result, an information asymmetry may make it more difficult for investors to get timely and reliable information about the company's performance.

- Management Quality: A small-cap company's ability to succeed is frequently determined by the calibre and skill of its management team. In certain instances, poor decision-making and underperformance might result from unskilled or inefficient management.

- Regulatory Risks: Smaller businesses could be more vulnerable to regulation changes, especially in heavily regulated sectors. The operations and profitability of the company may be affected by changes in rules.

- Corporate Governance: Certain small-cap firms might have less robust corporate governance frameworks, which could result in problems with accountability, transparency, and shareholder rights.

- Competitive Pressures: Larger, more seasoned competitors may present fierce rivalry for small-cap businesses. It can be not easy to compete successfully and increase market share.

- Market Timing Risk: In small-cap investing, timing is everything. Especially during market downturns, investing at the wrong time might result in considerable losses.

- Acquisition Risk: Smaller businesses may make more appealing acquisition targets, but there is no assurance that they will be bought. If there is no takeover deal, small-cap stocks may do poorly.

- Sector-Specific Risks: Certain industries can be more cyclical or susceptible to economic changes. Purchasing small-cap stocks in these sectors exposes investors to risks unique to the industry.

Risk Mitigation Technique for Small-cap Investing:

- Diversification: To spread risk, diversify across different small-cap equities or utilize small-cap mutual funds or exchange-traded funds (ETFs).

- Research and Due Diligence: To learn about a small-cap stock's competitive position, business model, and financial standing, thoroughly investigate and perform due diligence.

- Risk management: Establish your risk tolerance and put risk management techniques into practice, such as creating stop-loss orders and keeping your portfolio diversified.

- Long-Term View: Adopting a long-term investment perspective to weather short-term volatility and capitalizing on small-cap stocks' potential growth.

- Expert Advice: For direction and knowledge, speak with a financial advisor or investment specialist with experience in small-cap investing.

Although small-cap investing has its advantages, not all investors should pursue it. While considering these risks, matching your investment decisions with your financial objectives, risk tolerance, and investment horizon is critical.

2. Small-cap Investing Strategies

Strategies for investing in small-cap companies encompass a range of methods for choosing and overseeing these investments. Small-cap stocks present particular advantages and difficulties. These are a few typical small-cap investing techniques:

1. **Passive Small-cap Investing**: Invest in inexpensive index funds that follow small-cap indexes such as the S&P Small cap 600 or the Nifty Small cap 250. These funds offer a straightforward, hands-off strategy and broad exposure to the small-cap market.

2. **Active Small-cap Investing**:
   - **Bottom-Up Stock Picking**: Investigate and choose certain small-cap stocks using fundamental research. Seek out businesses with robust growth prospects, distinct advantages over competitors, and appealing valuations.

   - **Top-Down Approach**: Concentrate on small-cap industries or sectors predicted to perform well. Make appropriate investment allocations.

   - **Contrarian Investing**: Look for small-cap stocks that the market has sentimentally oversold or undervalued. The strategy's approach is investing in equities that are out of favour but may rise again.

   - **Quality Investing**: Look for small-cap firms with solid financial statements, consistent revenue growth, and room to develop. Quality-conscious investors place a high value on things like steady cash flow, little debt, and profitability.

3. **Factor-Based Investing**:
   - **Small-cap Value**: Invest in small-cap value equities that have high dividend yields and low price-to-book (P/B) and price-to-earnings (P/E) ratios. This approach looks for undervalued small-cap firms (Vogel, 2022).

- **Small-cap Growth**: Pay attention to firms with robust revenue growth prospects and good earnings growth. This strategy aims to profit from smaller, fast-growing enterprises' growth potential.

- **Momentum Investing**: Aim for small-cap stocks that have demonstrated a recent upward trend in price. Using this method, failing equities are sold and well-performing stocks are purchased.

- **Quality Factor**: Stress characteristics of small-cap firms that are associated with quality, like profitability, low debt, and steady profits growth.

- **Small Cap Contrarian:** Investors who are contrarians behave differently from the market. They look for small-cap stocks that have recently experienced losses or are out of favor. Buying while others are selling and spotting possible turnaround candidates are the goals.

4. **Thematic and Sector Investing**:
    - **Identify Growth Themes**: Invest in small-cap firms associated with particular growth themes or trends, such as consumer preferences, renewable energy, technology, or innovative healthcare.

    - **Sector Rotation**: Distribute funds throughout several small-cap sectors according to industry-specific trends and economic cycles. Consider concentrating on defensive sectors during recessions and cyclical ones during economic booms.

5. **Risk Management Strategies**:
    - **Diversification**: Distribute your money among various small-cap stocks to lessen the effect of risks unique to any company.

- **Stop-Loss Orders**: To reduce possible losses if the price of a small-cap stock drops, set predetermined exit points (stop-loss orders).

- **Position Sizing**: To control risk, carefully consider each small-cap investment's size about the entire portfolio.

6. **Long-Term Investing**:
    - Small-cap stocks can take some time to reach their full growth potential. Investing from a long-term perspective can help investors take advantage of compound gains while navigating short-term volatility.

7. **Dividend Investing**:
    - Take into account small-cap dividend equities with income and capital growth prospects. These equities could provide a safety net in times of market turbulence.

8. **Professional Guidance**:
    - Collaborate with financial counsellors or investment experts who focus on small-cap investments. Their knowledge can assist you in navigating this segment's complexity.

Selecting a small-cap investing strategy that fits your investment horizon, risk tolerance, and financial objectives is crucial. Although small-cap investing can be profitable, it also carries a larger volatility risk, so careful risk assessment and planning are essential. Additionally, when financial goals and market conditions change, frequently examine and modify your investment strategy.

3. Investment analysis approaches for small-cap investing

The distinct qualities and hazards connected with small-cap equities necessitate targeted and concentrated investment analysis techniques for small-cap investing. While evaluating small-cap firms, the following factors should be considered:

3.1 Fundamental Analysis:

- **Financial Statements**: Analyse the financial statements like the balance sheet, profit and loss statement and cash flow statement.
- **Valuation Metrics**: To find out the valuation of the firms use the valuation matrixes such as price-to-earnings (P/E), price-to-book (P/B), price-to-sales (P/S), and dividend yield (DY).
- **Earnings Growth**: Assess the company's potential for growth by analyzing its past and future earnings growth rates.
- **Competitive Position**: Evaluate the company's competitive standing in relation to its industry, considering its market share, entry hurdles, and competitive advantages.
- **Management Quality**: Analyse the management team's performance history, background, capacity to carry out the company's plan, and capacity for making decisions.
- **Profitability and Margins**: To determine the profitability of the business, examine measures such as operating margin, net profit margin, and return on equity.
- **Debt and Liquidity**: Analyse the debt to asset level of the firms and liquidity position.

3.2 Qualitative Analysis:

- Industry Analysis: Evaluate the firm's competitive position concerning the competing firms from that industry.
- Business Model: Analyse the fundamental business model of the firms, their competitive advantage and uniqueness of products and services.
- Management Team: Take into account the calibre and background of the organization's management group and their aptitude for carrying out the business plan.

- Corporate Governance: Look at the organization's board composition, transparency, and corporate governance policies.
- Market mood: The performance of the stock can be impacted by market mood and perceptions about the company.
- Search for Catalysts: Keep an eye out for prospective catalysts, such as the introduction of new products, the opening of new markets, or cost-effective initiatives.

3.3 Technical Analysis:

- Examine past price and volume data using technical analysis to spot trends, levels of support and resistance, and possible entry and exit points.
- Technical indicators that assist investors in choosing the right time to make small-cap investments include momentum oscillators, relative strength, and moving averages.

3.4 Growth vs. Value Analysis:

- Choose between concentrating on small-cap value companies and small-cap growth stocks. worth stocks are cheap in relation to their inherent worth, whereas growth stocks often offer significant potential for both sales and earnings growth.
- Examine the elements that are most crucial to your investing goals, then choose stocks that fit your strategy.

3.5 Macro and Micro Economic Analysis:

- Consider the larger economic landscape, including inflation, interest rates, and general market dynamics. Small-cap equities are susceptible to various effects from economic conditions than large-cap stocks.
- Examine the company's unique microeconomic aspects, such as its supplier chain, clientele, and market penetration.

3.6 Risk Assessment and Management:

- Analyse the particular risks connected to investing in small caps, including market, liquidity, and company-specific risks. Create a risk management plan that addresses position sizing, stop-loss orders, and diversification.

3.7 Long-Term Perspective:

- Invest with a long-term perspective to fully benefit from small-cap stocks' growth potential. Although tiny caps are prone to short-term volatility, they can yield substantial long-term rewards.

3.8 Stay Informed and Monitor: Keep a close eye on small-cap investments and be informed on news about the firm, the industry, and the overall state of the market. Review your investing thesis frequently and make any necessary revisions.

Investing in small-cap companies necessitates extensive study, careful consideration, and the capacity to evaluate a business's potential despite its tiny size. In the ever-changing world of small-cap investing, investors must match their investment analysis methodology with their financial objectives, risk tolerance, and investment horizon in order to make well-informed selections.

4. How to Invest in Small-cap Stocks

It is advisable to include small-cap investments in a diversified portfolio. By distributing risk across several asset classes, diversification lessens the impact of underperforming investments. A suitable percentage of the portfolio must be allocated to small caps in accordance with risk tolerance and financial objectives. Long-term investors are usually better suited for small-cap investing. Small-cap stocks are known for their increased volatility, which makes short-term price swings potentially quite large. Having a long-term perspective enables you to weather market fluctuations.

Purchasing small-cap stocks involves thoughtful planning, investigation, and analysis. This is a detailed instruction on how to buy small-cap stocks:

1. **Define Investment Goals**:
    - Decide your risk tolerance, investment horizon and liquidity requirements. Also, define the personal goals and time period by which you want to achieve those goals.
2. **Educate Yourself**:
    - Recognise the traits and dangers that come with small-cap stocks. Learn about important financial concepts such as earnings growth, market capitalisation, and valuation indicators.
3. **Open a Brokerage Account**:
    - Select a trustworthy brokerage platform based on what you require. Choose one that provides inexpensive trading fees, research tools, educational materials, and access to small-cap stocks.
4. **Conduct Research**:
    - Investigate possible small-cap assets in great detail. Make use of research reports, stock screeners, and financial news sources. Concentrate on fundamental analysis to evaluate the company's financial standing, competitive landscape, and growth possibilities.
5. **Diversify Your Portfolio**:
    - Invest your money across capitalisation, industries, companies and products.
6. **Risk Management**:
    - Clearly define suitable products that match your risk profile.
7. **Select Your Investment Strategy**:

- Select your investment pattern and types of firms you would like to hold in your portfolio.

8. **Consider Small-cap Funds**:
    - Investing in exchange-traded funds (ETFs) or small-cap mutual funds is a more diversified method.
9. **Stay Informed**:
    - Keep yourself updated with the market events and major macroeconomic events.
10. **Long-Term Perspective**:
    - Decide a time horizon of at least 5 years for small-cap investing.
11. **Avoid Emotional Decisions**:
    - Prepare the investment plan rationally.
12. **Seek Professional Guidance**:
    - Take guidance from professional fund managers.
13. **Tax Considerations**:
    - Calculate tax liability before exiting and rebalancing your portfolio. Take advantage of tax loss harvesting.
14. **Rebalance Your Portfolio**:
    - Continuously rebalance your portfolio to maintain asset allocation weights to optimum level.
15. **Record Keeping**:
    - Maintain account statements and cross-check your holdings at regular intervals.

While small-cap investing has the potential to expand, the risks are also higher. Approaching it with caution, diligence, and a well-defined plan is crucial. Make wise judgments and evaluate investments on a regular basis to help you reach your financial goals.

5. Small-cap Investment Vehicles

Investors can access and participate in small-cap equities through small-cap investment vehicles. These vehicles are available in a variety of shapes and sizes, each with unique features and specifications. These are typical investment vehicles for small caps:

5.1 Individual Stocks

Direct investing in small-cap stocks is possible if you use a brokerage account to buy individual business shares. With this strategy, you have total control over your assets, but it needs careful planning and observation.

5.2 Mutual Funds

By pooling investor capital, Small-cap mutual funds invest in a diverse range of small-cap stocks. Professional fund managers actively oversee them with the goal of achieving predetermined investment goals. Small-cap index funds, growth funds, small-cap value funds, and small-cap mix funds are among the mutual fund categories; each has a unique investment strategy (Keim, 1999).

- **Small-cap Index Funds**: Index funds follow a certain market index, like the S&P SmallCap 600, in a passive manner. Their goal is to duplicate the performance of the index. minimal costs and minimal turnover are hallmarks of index funds.

- **Small-cap Sector Funds**: Sector-specific mutual funds or exchange-traded funds (ETFs) concentrate on small-cap stocks in a given sector or industry. Some examples are small-cap funds for the technology, healthcare, and finance sectors.

- **Small-cap Value and Growth Funds**: • Undervalued small-cap equities with low P/E and P/B ratios and high dividend yields are the focus of small-cap value funds. Small-cap growth funds focus on small-cap businesses with significant potential for profits growth.

- **Small-cap Dividend Funds**: These funds concentrate on dividend-paying small-cap equities. Small-cap dividend funds may appeal to investors looking for income and possible capital growth.

5.3 Exchange-Traded Funds (ETFs)

- While small-cap ETFs trade on stock exchanges like individual stocks, they are comparable to mutual funds. Usually, they follow small-cap indexes like the Nifty Small Cap 250 Index.

- When it comes to mutual funds, exchange-traded funds (ETFs) have reduced expense ratios, transparency, and liquidity.

5.4 Small-cap Unit Investment Trusts (UITs):

- UITs and mutual funds are comparable, except UITs have a predetermined portfolio of securities. With a particular investing goal, small-cap UITs may hold a diverse portfolio of small-cap companies.

5.5 Small-cap Real Estate Investment Trusts (REITs):

- Tiny-cap Small real estate assets, including retail stores, residential buildings, and industrial facilities, are the focus of REITs. These vehicles provide investors with access to the real estate industry.

5.5 Small-cap Index Options:

- Sophisticated investors can engage in speculative or hedging activities with options contracts based on small-cap stock indices, including the Russell 2000 Index.

5.6 Small-cap ADRs (American Depositary Receipts):

- Certain overseas small-cap companies trade as ADRs on U.S. marketplaces. You can purchase foreign small-cap stocks by investing in small-cap ADRs.

5.7 Small-cap Robo-Advisors:

- A few robo-advisors provide small-cap stock portfolios. These automated investing platforms build and maintain portfolios according to your financial objectives and risk tolerance.

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When selecting one of these small-cap investment vehicles, investors should carefully assess their investment goals, risk tolerance, and preferences.

6. Risks and Challenges

Although small-cap investing comes with many benefits, there are certain challenges that investors should take care of:

- **Economic Sensitivity:** Small-cap stocks are more volatile during turbulence in the market and economy
- **Lack of Information:** At time availability and accuracy of information is an issue for small cap companies. A large number of analysts do not cover them.
- **Company-Specific Risks:** Small-cap firms are opaque and face higher company-specific risks because economies of scale are not working in favor.
- **Volatility**: Small-cap stocks are more volatile, which may result in large losses.
- **Lack of Liquidity**: Small-cap stocks have lower trading volumes and limited liquidity. Higher transaction costs and broader bid-ask spreads may follow from this.
- **Market Risk**: Small-cap equities are susceptible to the state of the market as a whole. Due to their potential lack of the financial stability of larger corporations, small-cap stocks are more susceptible to economic downturns and bear markets.
- **Financial Risk**: Smaller businesses may be more susceptible to financial hardship because they frequently have fewer financial resources. They can have trouble paying off debt and getting access to capital markets.
- **Lack of Diversification**: Smaller businesses tend to be less diversified than larger enterprises since they may only serve certain markets or sectors of the economy. This may expose investors to dangers unique to a given industry.

- **Information Asymmetry**: It's possible that analysts and institutional investors pay smaller businesses less attention than they do larger ones. As a result, there may be an information asymmetry that makes it more difficult for investors to get timely and reliable information about the performance of the company.

- **Management Quality**: A small-cap company's ability to succeed is frequently determined by the calibre and skill of its management team. Underperformance and poor decision-making can result from inexperienced or inept management.

- **Regulatory Risks**: Smaller businesses could be more vulnerable to changes in regulations, especially in heavily regulated sectors. The operations and profitability of the company may be affected by changes in rules.

- **Corporate Governance**: Certain small-cap firms might have less robust corporate governance frameworks, which could result in problems with accountability, transparency, and shareholder rights.

- **Competitive Pressures**: Larger, more seasoned competitors may present fierce rivalry for small-cap businesses. It can be difficult to compete successfully and increase market share.

- **Market Timing Risk**: In small-cap investing, timing is everything. Especially during market downturns, investing at the wrong time might result in large losses.

- **Acquisition Risk**: Smaller businesses may make more appealing acquisition targets, but there is no assurance that they will be bought. If there isn't a takeover deal, small-cap stocks may do poorly.

- **Sector-Specific Risks**: Certain industries might be more cyclical or susceptible to fluctuations in the economy. Purchasing small-cap stocks in these sectors exposes investors to risks unique to the industry.

Investors ought to think about the following tactics in order to lessen these risks and difficulties:

- **Diversification**: To diversify your investments and reduce risk, choose small-cap mutual funds or exchange-traded funds (ETFs).
- **Research and Due Diligence**: To comprehend a small-cap stock's competitive position, company strategy, and financial health, thoroughly investigate and perform due diligence on each one.
- **Risk Management**: Establish your risk tolerance and put risk management techniques into practice, such as creating stop-loss orders and keeping your portfolio diversified.
- **Long-Term Perspective**: If you want to take advantage of small-cap stocks' potential growth while weathering short-term volatility, think about investing for the long run.
- **Professional Advice**: To ensure you make well-informed investing decisions, speak with a financial professional or carry out independent research.

Although small-cap investing has its advantages, not all investors should pursue it. It is crucial to approach it with caution, care, and a well-defined risk management plan that fits the investor's risk tolerance and financial objectives.

7. Small Cap Investing: Performance Analysis of and Factor Investing

Small-cap stock investing has a proven track record of success and provides a number of benefits for investors (Loeb, 1991). Historical data indicates that small-cap investment can be a successful strategy, even though previous performance does not guarantee future outcomes. The following are some important things to think about while evaluating the proof that small-cap investing is successful:

Historical Outperformance: In terms of returns over the long haul, small-cap companies have frequently beaten large-cap ones. Numerous research investigations and analyses have demonstrated that on average, small-cap stocks have produced stronger returns than their larger counterparts.

Risk-Return Profile: Small-cap stocks are usually linked to higher risk levels because of their smaller size and increased price volatility. However, the possibility of greater rewards may offset this risk. Investors looking for growth prospects may find this risk-return trade-off appealing.

Market Inefficiencies: Analysts and institutional investors tend to study smaller companies less attentively than large-cap equities. This may result in undervalued or mispriced small-cap equities, which would cause market inefficiencies. Those with experience in investing can spot these chances and take advantage of them for bigger profits.

Long-Term Wealth Creation: Significant wealth can be created over time by making long-term investments in small-cap stocks with excellent growth potential. Compounding's power can increase the profits from profitable small-cap investments.

Economic Growth Sensitivity: Small-cap businesses are more likely to be responsive to local economic situations since they are frequently more integrated into the home economy. Small-cap stocks may do well during economic expansion and growth, allowing investors to profit from these developments.

Acquisition Targets: Smaller businesses that offer distinctive services, goods, or technologies may get the attention of larger organisations looking to acquire them. If an acquisition bid is made, this could lead to a significant increase in the stock price.

Diversification Benefits: Small-cap stocks can increase diversification, lower total portfolio risk, and perhaps increase risk-adjusted returns when included in a diversified portfolio.

It is crucial to remember that investing in small-cap stocks has its share of difficulties, such as increased volatility, liquidity risk, and the possibility of financial instability in certain tiny businesses. Therefore, before adding small-cap stocks to their portfolios, investors should carefully assess their investing horizon, risk tolerance, and diversification approach. Furthermore, choosing specific small-cap companies or thinking about investing in small-cap mutual funds or exchange-traded funds (ETFs) requires extensive research and due diligence because the success of small-cap investing is not assured. Furthermore, while negotiating the complexity of small-cap investment, the guidance and experience of a financial professional can be quite helpful.

The process of incorporating a small-cap focused strategy into a smart beta or factor-based investing method entails creating a systematic, rules-based investment plan that focuses on the special qualities and benefits of small-cap stocks (Blitz and Vidojevic, 2019). Smart beta methods aim to transparently and economically capture certain investment themes or characteristics. Here's how to apply smart beta principles to construct a small-cap focused approach:

- **Factor Selection**:
  - Select the precise elements or traits you wish to focus on in the small-cap market. Three common variables are quality, momentum, and value in small-cap investing.
  - You may choose low price-to-earnings (P/E) ratios, low price-to-book (P/B) ratios, and high dividend yields for a small-cap value strategy.
  - You may take into account recent price performance and earnings momentum while implementing a small-cap momentum approach.
  - For a small-cap quality approach, you may concentrate on elements like profitability, low debt levels, and steady earnings growth.

- **Index Construction**:
    - In the small-cap universe, create an index or choose an already-existing smart beta index that reflects the specified factor strategy.
    - Assign a weight to each stock in the index according to the chosen criteria. For instance, stocks with lower P/E ratios may be given larger weights in an index that prioritises value.

- **Rebalancing Rules**:
    - Create guidelines for routine rebalancing in order to keep the targeted factor exposure. This could be carried out quarterly, semi-annually, or annually.
    - To preserve factor exposure, rebalance the index by purchasing inexpensive or outperforming companies and selling overpriced or underperforming ones.

- **Risk Management**:
    - Use risk management techniques to reduce unforeseen hazards in the portfolio, such as limiting sector exposures or individual stock concentrations.
    - Establish exit or stop-loss criteria to guard against large losses on particular stocks.

- **Cost Management**:
    - Consider transaction costs and reduce portfolio turnover to keep trading costs to a minimum.
    - To implement the idea, use inexpensive investment vehicles like index funds or exchange-traded funds (ETFs).

- **Backtesting and Simulation**:
    - Perform extensive simulations and backtesting to assess the small-cap smart beta strategy's risk profile and past performance. This makes the plan more likely to meet your goals and expectations.

- **Implementation Vehicles**:
    - Decide which investment vehicles to use to carry out the plan. Options include employing current small-cap smart beta mutual funds or exchange-traded funds (ETFs) or building a tailored portfolio of individual stocks.

- **Monitoring and Rebalancing**:
    - Regularly check the smart beta portfolio's performance and factor exposure.
    - Rebalance the portfolio on a regular basis to keep the intended level of risk and factor exposure.

- **Review and Adjust**:
    - Regularly assess the strategy's effectiveness and make any required modifications. This could entail risk management strategies, rebalancing guidelines, or factor improvement.

- **Educational Resources**:
    - Keep up with the most recent findings and innovations in smart beta and factor-based investing. Information can be found in industry publications, academic studies, and investment conferences.

Remember that putting into practice a smart beta strategy necessitates a methodical and disciplined approach, whether centered on small caps or any other element. It's critical to comprehend your investing objectives, risk tolerance, and the particular variables you want to focus on. Getting advice from financial advisors or factor-based investment specialists might be helpful when developing and overseeing smart beta strategies. Note that these numbers are subject to change over time.

Below is a simplified tabular comparison of the typical risk and return characteristics of various groups:

Aspect	Large Cap Portfolio	Mid Cap Portfolio	Small Cap Portfolio
Risk	Lower	Moderate	Higher
Historical Returns (e.g., CAGR)	12-15% (approx.)	15-18% (approx.)	18-20% (approx.)
Volatility (Standard Deviation)	12-15% (approx.)	18-22% (approx.)	20-25% (approx.)
Correlation with Market	High	Moderate	Low to Moderate
Liquidity	High	Moderate	Moderate to Low
Market Capitalisation Range	Above 20,000 Crore	From 5,000 to 20,000 Crore	Below 5,000 Crore
Investment Horizon	Moderate to Long-term	Moderate to Long-term	Long-term

Please be aware that these numbers are estimates and could change depending on the individual equities in the portfolio, the state of the economy, and market trends. When contemplating investments in various market cap segments in India or any other market, thorough study and analysis are necessary, as these portfolios' risk and return profiles are subject to fluctuations over time. Furthermore, the selection of portfolio composition should be guided by investing objectives and risk tolerance. When choosing investments, it is advisable to speak with a financial professional or thoroughly examine past performance and risk measures.

Small Cap Indices:

Small-cap indices monitor the performance of small-cap companies in numerous global marketplaces. These indices give investors a standard by which to compare the performance of small-cap companies across several nations or areas. Here are a few well-known small-cap indices from different geographical areas:

1. **Russell 2000 Index (USA)**: One of the most watched small-cap indices in the US is the Russell 2000 Index. It monitors the success of the Russell 3000 Index's 2,000 smallest businesses.

2. **S&P SmallCap 600 Index (USA)**: S&P Dow Jones Indices developed this index, which evaluates the performance of 600 US small-cap firms drawn from the S&P 1500 Index.

3. **FTSE SmallCap Index (UK)**: Small-cap stocks that are listed on the London Stock Exchange are represented by the FTSE SmallCap Index. It belongs to the smaller FTSE All-Share Index subgroup.

4. **Nikkei Jasdaq Index (Japan)**: With an emphasis on emerging businesses, the Nikkei Jasdaq Index follows small-cap stocks on the Tokyo Stock Exchange's Jasdaq market.

5. **FTSE SmallCap Japan Index (Japan)**: This index is a subset of the larger FTSE Japan Index series and reflects small-cap firms that are listed on the Tokyo Stock Exchange.

6. **STOXX Europe Small 200 Index (Europe)**: As a member of the STOXX Index family, this index monitors the performance of 200 small-cap firms in Europe.

7. **Nifty 250 Small-cap Index (India)**: The NSE Small-cap Index maintains the performance of small firms listed on the National Stock Exchange.

8. **SSE 180 Index (China)**: A popular small-cap index in China that tracks the performance of small-cap stocks on the Shanghai Stock Exchange is the SSE 180 Index.

These are but a handful of instances of small-cap indices from various global locations. Investors and fund managers use each index with its own methodology and selection criteria for small-cap stocks to assess how well small-cap segments within different markets are performing. Exchange-traded funds (ETFs) and mutual funds that let investors participate in small-cap companies across different geographic areas are frequently built on small-cap indices.

Example of some of the Small Cap Mutual Funds in India:

1. HDFC Small Cap Fund
2. Reliance Small Cap Fund
3. SBI Small Cap Fund
4. DSP Small Cap Fund
5. Axis Small Cap Fund
6. Aditya Birla Sun Life Small & Midcap Fund
7. ICICI Prudential Small-cap Fund
8. Kotak Small Cap Fund
9. Franklin India Smaller Companies Fund
10. Invesco India Small-cap Fund
11. UTI Small Cap Fund
12. Nippon India Small Cap Fund
13. IDFC Small Cap Fund
14. Tata Small Cap Fund
15. BNP Paribas Small Cap Fund
16. Motilal Oswal Small Cap 35 Fund
17. Edelweiss Small Cap Fund

8. Conclusion

To sum up, small-cap investing refers to purchasing stocks in businesses with comparatively tiny market capitalisations. For investors, small-cap companies present unique opportunities as well as difficulties. It is crucial to evaluate an investor's risk tolerance, investing objectives, and overall portfolio strategy prior to making any investments. A diversified portfolio can benefit from the inclusion of small-cap investments, provided they are made with a deliberate and informed approach (Eun et al., 2008).

When it comes to investment and portfolio management, business size matters since it affects diversification, risk and return, and alignment with your investing goals. To balance risk and possible rewards, many investors decide to include a mix of large-cap, mid-cap, and small-cap companies in their portfolios. The precise combination, however, ought to be determined by each investor's risk tolerance and financial objectives.

While small-cap stocks offer benefits, it's crucial to remember that they also present particular difficulties, like increased market volatility, liquidity risk, and the possibility of financial instability in certain businesses. Hence, Small-cap investing should be selected carefully after considering investor’s risk profiling. Typically, a well-diversified portfolio should include firms across capitalization like large, mid and small caps firms. In small-cap investing, winning strategy depends on due diligence, a well-formulated investment strategy, and consistently following the investment plan, irrespective of market movements.

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Chapter 3

QUALITY INVESTING: LOOKING FOR VALUE IN QUALITY STOCKS

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Abstract

Quality investing is the use of a company's fundamental qualities to curate strategies for superior returns in the long term. However, measuring quality is complex due to inconclusive opinions on factors that determine high quality. Quality has multiple dimensions: profitability, earnings quality, safety, investment, profitability, leverage, and operating efficiency. The metrics of quality investing have grown from Lev & Thiagarajan's 12 signals, Graham score, Sloan ratio to recent advents of Piotroski F score, Grantham score, and Greenblatt Magic formula. Even in India, quality investing consistently outperformed by withstanding long-term economic shocks despite factors like US sovereign rating downgrades, taper tantrums, and the COVID-19

pandemic. This chapter will review quality investing metrics, strategies, and indices in a global and Indian context.

1. Introduction

Investment in a portfolio requires the investor to pick stocks based on various fundamental and price signals to make the portfolio sound and robust and deliver consistent returns. This gives us an essential understanding of an investor's investment style while building the portfolio. An investor analyses many factors before deciding on the investment avenue. These factors are prudent to understand the risk-return matrix offered by the investment. Risk mitigation and returns are an outcome of the investment style adopted. This process is known as factor investing. Investors will pick stocks based on specific attributes such as quality, volatility, momentum, value, and size in factor investing. There is an economic rationale for the existence of these factors and a reason for them to persist. Two styles are predominantly popular amongst investors - Value and Growth. It is impertinent to understand the difference between these styles.

Value Investing: This is used to understand the fair value of a company's stock. Benjamin Graham, David Dodd, and Warren Buffet believe in this method.

Growth Investing: Unlike value investing, growth investing compares the current stock price with historical prices. This comparison is made to analyze the company's growth potential. It usually picks stocks that are highly priced and have higher growth potential. This method believes that a stock's current price reveals the company's actual value/ worth.

Investors chase returns and hence include high-performance stocks, i.e., stocks that have given good returns in the past quarter or year. The reason for this is the belief that if a stock has performed well in the past, it will continue to do so. Similarly, stocks that have diminished in value and are in red are excluded. This is known as momentum investing.

When we use the word quality, the term is self-explanatory yet undefined. One prefers a better-quality product at a reasonable price than paying the same price for a low-quality product. This holds for any subject in discussion. The question is, how does one define quality when it comes to investing? Academic research shows that a portfolio that includes stocks based on quality factor tends to perform better than a portfolio strategy based on growth and value. In recent times, Factor investing has seen an upsurge, and therefore it would seem easy to segregate the quality factor into a rateable metric. Quality investing, however, is more complex than it sounds. This is because having a commonly acceptable definition of quality takes time and effort. There is no single definition of quality. Portfolio managers use various systems of measurement and methodologies to build a portfolio based on quality. Quality strategy may include various metrics, such as choosing a stock with a high return on equity, low leverage, and steady earnings. Quality investing is looking beyond the company's earnings and having a vision of the earning power of the company. It is going beyond the numbers and analyzing the company moat, business model, brand value, and the management and governance of the company.

There is a close connection between quality investment style and factor investment. Through a quality investment strategy, portfolio managers try to segregate companies capable of performing better than their peers and having consistent returns during market downturns. This investment style is appropriate for investors with equalized risk-taking capacity and a long-term investment horizon. Efficient allocation of money is a prudent factor in categorising a company as a quality investment. This is because a company that can efficiently earmark its capital tends to have stable financial statements that make it financially healthy. However, constructing a strategy based on quality needs assessment of many factors. These factors include ranking the companies with their peers based on analysis of quantitative and qualitative factors, sectoral allocations, etc.

Portfolio managers can change the percentage of capital allocated to the sectors depending on the analysis of the quantitative factors. This way, capital allocation in various sectors can be restricted as the benchmark index. The portfolio covers all the superior-quality stocks. This in turn, allows the investor of the portfolio to profit from all the best-quality stocks without making any speculations.

The ranking process allows a peer-to-peer comparison between stocks from the same industry based on various qualitative and quantitative factors. This helps the portfolio manager in the stock selection process.

This chapter will provide an understanding of quality investing by reviewing the quality indicators and evaluating the performance of this investment style. This chapter is organized as follows: Section 2 will review prominent quality indicators, including their premise. Section 3 will present a holistic review of the performance of quality investing. Section 4 will illustrate the performance of global and Indian quality indices, which the conclusion will follow.

2. Review of Quality Indicators

The concept of quality investing was introduced in 1934 by Benjamin Graham when he tried to understand which stocks exemplify quality stock. Benjamin Graham and Warren Buffet also spoke about quality and value investing. Warren Buffet has famously said that it is better to buy quality stock at a reasonable price than to buy average stocks at a price that has a good value. There was a distinction between stocks that were available cheaply and stocks with quality attributes. Even within stocks with quality attributes, some stocks were of superior attributes as compared to others. Despite this, there was no clear-cut explanation for describing quality investing. Ever since then, quality investing has been described with varied perspectives.

Quality indicators began as simple financial indicators in the form of financial ratios. Financial ratios enable the assessment of companies with regard to various dimensions like profitability, asset management, liquidity, and long-term solvency (Endri et al., 2020). The below provides a cursory view of the dimensions presented by financial ratios.

Table 1: List of financial ratios used as quality indicators

Category	**Ratios**
Profitability	Gross Profit Margin, Operating Profit Margin, Net Profit Margin, Return on Investment, and Return on Equity
Solvency	Debt Ratio, Net Debt to Equity Ratio, Interest Coverage Ratio and Debt Coverage Ratio
Efficiency	Tangible Asset turnover, Total Asset Turnover, Inventory Turnover, and Working Capital Turnover
Growth & Stability	Sales growth, EPS growth, Stability of EPS growth, Stability of cash flow profitability

(Source: Prepared by authors from https://shodhganga.inflibnet.ac.in:8443/jspui/handle/10603/373210, accessed Oct 28, 2023)

Despite the availability of financial ratios, consensus on quality indicators was not achieved. Combining these financial ratios led to the ideation and creation of new indicators. Comprehensive indicators were created using an inductive or scoring approach. This multi-ratio score or values were expected to capture the various quality dimensions and provide the user with the required information.

- Graham's G-score: In the early 1950s, Graham identified seven quality signals. These quality and quantity criteria focused on parameters such as the size of the company, healthy current ratio, consistent earnings, dividend payment history, earnings growth, price-to-earnings ratio, and price-to-assets ratio.

  Robert Novy Marx (2014) re-created the Graham Score using five quality criteria. Each criterion is assigned 1 point. This way, the score will be 0 to 5, where five is the highest. A higher score is an indication of higher quality asset selection. Points are allotted if the long-term debt is less than current assets, net earnings in the past ten years have been positive, current assets are more than double the current liabilities, and the last ten years' dividends and buybacks should be positive, as compared to 10 years, the current year earnings should be at least 33% higher.

- Lev & Thiagrajan: Their study identified Twelve fundamental signals to improve the explanatory ability of incremental earnings. The signals were identified with the aid of written pronouncements from financial analysts. These twelve signals are Capex, R&D, inventory, gross profit, selling and administrative expenses, provision for doubtful debtors, accounts receivable, LIFO earnings, order backlog, and audit qualification. The study established a significant relationship between the 12 signals on the annual excess stock earnings (Lev and Thiagarajan, 1993).
- Grantham's Quality: Grantham suggested that companies with a low debt-to-equity ratio, higher profitability, and low fluctuation in earnings growth tend to do better in the long run. Companies with low debt-to-equity ratios tend to outperform companies with high debt-to-equity ratios.
- Sloan's Earnings Quality: This strategy was incorporated by BlackRock. The factor is calculated using Net income, cash flow from operating activities, Cash flow from investing activities, and Total assets. Kozlov and Petajisto (2013), in their paper "Global Return Premiums on Earnings Quality, value and Size" promote the excess return-generating ability of the strategy by combining it with the Value strategy.
- Piotroski F-Score: Initially, the F-Score was tested amongst value stocks due to its ability to perform fundamental analysis. However, the F score may not be limited to high book-to-market ratios, as it captures information about a firm's fundamental strength or quality, making it a return-predictive device. There are nine criteria in the F Score. It uses both Grantham's quality measures, Sloan's earnings quality, and fundamental momentum. Four criteria capture profitability, three capture liquidity, and two capture operational efficiency. Each component scores 0 – indicating weakness or 1 -indicating strength.

Thus, the score ranges from 0 to 9., where 9 is the highest score (Piotroski, 2002).

- Defensive Equity: This is an investment strategy that aims to provide returns that are similar to equity markets but with less amount of risk. Stocks of companies that have shown exemplary financial health and are less volatile than their peers are bought under this strategy. Due to low risk, these strategies generally perform better during volatile markets.
- Joel Greenblatt: The study emphasized the use of the return on invested capital (ROIC) parameter in quality investing along with valuations, which was also popularly referred to as the "Magic Formula" (Ahuja & Jain, 2017)
- Mohanram G score: The G score is a numeric tool developed by Mohanram in 2005 to identify value gainers and losers in BM firms. The score is awarded one if a company's component value is favorable compared to the median value of sectorial peers. The factors include Return on Assets, Cash Flow Return on Assets, CFO to Net Income, Earnings Variability, Sales Growth Variability, Advertising Expenses, Capital Expenditure, and Research and Development Expenses (Mohanram, 2005).

Despite the above list, many more tools for fundamental evaluation are also used as quality indicators. Altman Z score, Montier C score, Beneish M score, and Kralicek model, amongst many others. This proves how quality is an undemarcated phenomenon with no lead indicator.

3. Evidence and explanation of the success of quality investing

Quality has a weak consensus among traditional equity factors due to its reliance on financial reporting data, a market and accounting data combination, and the broad scope of possibilities for evaluating a company's quality features. This section presents a brief review of key literature highlighting the use of different quality indicators in different economies using varied methodologies to evaluate the return-generating ability of quality investing.

The most recent advent in quality indicators is the Piotroski F score. The tool created 2002 has been considerably researched and proven to provide superior returns. The metric has been examined in value stock subsamples or conjunction with other factors, including momentum and book-to-market. Tikkanen and Äijö (2018) discovered that European long-only value investing techniques may be considerably enhanced by utilizing F score information. Walkshäusl (2017) and Piotroski and So (2012) all discovered a significant performance-related interaction between F score and all book-to-market ratios, including growth and value stocks. Their findings indicated that positive value-growth returns were concentrated between growth stocks with low F scores and value companies with high F scores. Walkshäusl (2020) examined the return predictive ability of the F-score across 20 developed non-US markets and 15 emerging markets in a comprehensive analysis from 2000-2018. The study concluded that F score premium is a worldwide occurrence with the capacity to forecast returns in both developed and emerging markets.

Another metric for quality investing is the Magic formula. Davydov, Tikkanen, and Äijö (2016) compared the most common value investing strategies in the Finnish Stock Market from 1991 to 2013 using a magic formula and its variation, i.e., the cash-flow enhanced magic formula. The top 30% of stocks were ranked using ROIC and EV/EBIT ratios. Carhart's four-component model was used to capture aberrant returns, and risk-adjusted performance measurements included Sortino and Sharpe ratios. Between 1991 and 2013, an average yearly return of 19.3% was found for both strategies. EBIT/EV had the highest Sharpe ratio, followed by the magic formula, P/E, and cash-flow augmented magic formula. The tool was also tested in the Indian market by Preet et al. (2021) over eight years from 2012 to 2020. The method ranks firms based on their P/E and ROCE, adding them to create a combined score. The 30 companies with the lowest joint score were selected to create an evenly weighted portfolio. In five of the eight years, the Magic

Formula portfolio beat the market with a compound annual growth rate (CAGR) of 9.31% as opposed to 13.89% for the BSE Sensex.

Novy Marx shattered a misconception that quality indicators must be complex in his 2013 paper "The Other Side of Value: The Gross Profitability Premium." The study not only provided explanations regarding superior performance but also gave new insights into the cross-section returns of stocks by introducing another dimension to value: quality. The paper identified a quality measure that can predict cross-section stock returns as much as any other factor. This quality factor is Gross Profitability, defined as revenues minus cost of goods sold divided by total assets. This factor is used to look for quality assets. This is a good factor compared to earnings, which can be manipulated. The author says gross profit is the most unadulterated measure of economic profitability. The study tested the role of gross profitability with a variation of the four-factor model. The performance of the model improvement is primarily due to the profitability factor, with only one-third attributed to industry adjustments to value and momentum factors. DFA and AQR Capital management use this design to construct their funds.

Further, the author tested various quality metrics in the US, including Sloan's accruals, Greenblatt's ROIC, Grantham's quality score, Graham's G-score, defensive investor strategy, and gross profitability and earnings quality (Novy-Marx, 2014). Using data from 1963 to 2013, the study constructed quality portfolios using seven indicators. A three-factor model tested strategies with significant alphas, all negative market factors, and large-cap stocks. Spanning tests showed positive abnormal returns, with gross profitability and Grantham's quality score generating significant positive alphas. When combined with quality metrics of ROIC, F-score, and gross profitability, values investing generated higher alpha in large cap universe. The best-performing methods were gross profitability, F score, ROIC, and Grantham's quality score.

Following the essence of the previous paper, Lalwani & Chakraborty (2018), analyzed quality investing in the Indian stock market using metrics almost similar to the previous paper. Grantham's quality score, magic formula, Piotroski's F score, and gross profitability were the indicators used. The study used the BSE-500 index from 2001-2016, focusing on nonfinancial companies. Long-only portfolios were constructed for these metrics, with the top 30% per ranking. Daily stock returns were taken, and risk-adjusted performance was studied using the Sharpe ratio, Carhart's four-factor model and CAPM. After adjusting for size, value, and momentum, the findings indicate that gross profitability and the Grantham quality score produced higher results. Piotroski's F-score performed the poorest, underperforming the market.

A similar study with differentially structured indicators was performed by Lepetit et al. (2021), who defined quality along four dimensions: profitability, earnings quality, safety, and investment, each described by two fundamental metrics. Each metric is converted into percentiles at the end of each quarter, with the highest percentile allocated to the highest quality company. The metric level quality score equals the z-score. In contrast, the dimension level quality score is calculated by averaging the two metrics and converting the resulting percentile into a z-score. Quarterly non-sector-neutral portfolios in five regions, consisting of thirteen subsets, were created. Companies are categorized into high-quality (Q1) and low-quality (Q5) quintiles. Long-only and long-short factor-mimicking portfolios are formed, value-weighted based on MSCI market capitalization, and rebalanced quarterly. The quality factor in institutional investors' portfolios has shown significant alpha over the past 18 years, outperforming conventional equity factors. The factor outperforms its benchmark by 2.8% annually, with an information ratio of 0.81. Safety is paramount during market turmoil, and sector-neutral portfolio construction suits the Eurozone. A new portfolio construction methodology uses a K-means algorithm clustering approach to capture dynamic variations between fundamentals and other stock features, resulting in better quality factor performance.

The premise that quality indicators need to be financial was tested by Edmans (2011). The study supported human relations theories that employee happiness boosts company success through motivation, retention, and recruiting. This study investigates the relationship between long-term stock returns and employee happiness. A value-weighted portfolio, including the 100 Best Companies to Work For in America, produced an annual four-factor alpha of 3.5% between 1984 and 2009, 2.1% higher than industry benchmarks. Positive earnings surprises and announcement returns were more prevalent among Best Companies, implying a favorable correlation between shareholder returns and employee happiness.

The argument over whether accruals quality, or accounting information quality, is a priced risk factor was expanded by Bandyopadhyay et al. (2015). Earnings management is crucial for the stock market since it may provide insight into how a financial market may seem. Furthermore, mispricing in the stock market brought on by cash flows and accruals might result in a high or low value for the companies. Since investors rely on private information when no public information is available, accounting quality is seen as a type of information risk that can result in greater returns. Investors may find it challenging to predict a company's future performance when accruals are poor quality, increasing information risk. The accruals quality ("AQ") metric from Dechow and Dichev (2002) was calculated using the yearly data of all companies listed on the NYSE, NASDAQ, or AMEX. The study showed a strong inverse relationship between accruals quality (AQ) and future returns. The return premiums linked to AQ are robust to three Fama-French factors: price momentum, illiquidity, earnings momentum, and earnings yield.

Asness et al. (2019) defined quality as characteristics investors should pay a higher price for, revealing that high-quality stocks deliver high risk-adjusted returns, while low-quality junk stocks deliver negative returns. High risk-adjusted returns can be obtained by investing in long-quality companies and short junk stocks through a quality-minus-junk (QMJ) portfolio. The QMJ factor yields substantial risk-adjusted and positive returns in 23 24 nations. It comprises the top 30% of high-quality stocks and the bottom 30% of trash stocks. QMJ portfolios defy risk-based explanations based on correlation with market crises since they have positive alpha, negative exposure to the market, value and size, and good returns during market downturns. Although they are more expensive and risky than trash stocks, quality equities have a low beta and profit from a flight to quality during severe market hardship. The price of quality shows the asset pricing conundrum, which forecasts the return to the QMJ factor.

A review of 40 such literature on investment strategies found that 8 out of 9 factors reported had positive returns, with five statistically significant. However, measures with positive returns are more likely to be published. The literature highlights data-snooping and biases in the publication process, with 51% of 600 factors working after publication and 49% failing. The long list of quality variables facilitates data mining and impedes independent verification of factor effects. Each product offering captures the supposed factor uniquely, leading to inflated practitioner-supplied returns for quality strategies. Therefore, a healthy skepticism is recommended when discussing quality strategies (Vitali Kalesnik, 2016).

4. Cases of quality investing: Global & India

Quality investing has grounded roots in concept and academic literature. With multiple metrics available for identifying quality stocks, the investing style held colossal potential. Multiple indices have cropped up to identify and assess the performance of a basket of quality stocks. From the 2010s, major index providers like MSCI, FTSE Russell, Standard & Poor's, Research Affiliates, EDHEC, and Deutsche Bank developed smart beta indexes based on quality factors. These indexes are often marketed as independent sources of return and diversification due to their low correlation with value (Hsu et al., 2019).

The National Stock Exchange of India and the Bombay Stock Exchange also launched quality-centric multiple indices in 2012. NSE launched seven indices with a single quality factor or multifactor with other styles. NSE uses Return on Equity, Debt to Equity, and Earnings growth variability as a metric for the identification of quality stocks. These indices have generated an average return of 11%. Bombay Stock Exchange and S&P launched a quality index based on screening stocks from BSE-listed companies. The index uses Return on Equity, Debt to Equity, and Accruals ratio to identify quality stocks. The index generated an average return of 11.75%.

Figure 1 presents the performance of five NSE indices and one BSE index regarding annual return. The indices have generated returns as low as -1.79% to as high as 42.24%.

Quality Indices have weathered the pandemic crisis as well. In the pandemic years, only two indexes also fell into negative; others stayed afloat. This lets us conclude that flight to quality might be a worthwhile strategy in an economic crisis. In the backdrop of recovery, the indices did not lag; the BSE Quality Index had an annual return of 42.24%, followed by 38.41%, which generated a return of 38.41%.

Figure 1: Performance of Indian Quality Indices

(Source: Author's working)

Annexure A presents an assortment of quality indices for a comparative view of Indian and global quality indices. From a cursory glance at the table, it is evident that the quality indices have generated marginally superior returns to their respective benchmark. This validates the need for the identification of metrics for quality investing. One year's return of most global indices has stayed above 20%, whereas, in India, they have mostly stayed below. However, for Indian indices, the returns have stayed relatively more consistent than their global counterparts. Returns of all the global indices fell from the first year to the fifth year on an average of 16%. The return drop from years 1 to 5 in India is 3%. This shows that Indian quality stocks can persistently perform better.

Starting with the metrics of quality stock identification, it can be seen that NSE uses the same metrics that MSCI uses. In contrast, BSE uses the metrics followed by S&P. Academic studies highlight profitability, accounting quality, payout/dilution, and investment as critical factors. However, earnings stability, capital structure, and profitability growth should be more researched.

Though it allows for assurance of return generation, this methodology would limit the proliferation of testing different quality perspectives. As mentioned in the previous two sections, multiple quality metrics exist; merely replicating two indicators and differentiating on one does not display the utilization of the full spectrum of quality investing.

Another distinctive feature is the beta of Indian NSE indices against the global index. The global MSCI indices have an average 0.91 beta, representing low differentiation from the parent index. NSE quality indices have a beta of 0.7, representing a better differentiation. Such differentiation is necessary for the return generation ability of the factor-based and parent indexes to differ significantly and for the investing style to retain relevance. Thus, Indian quality indices have a better beta, permitting them to be used as hedges for the long term.

5. Conclusion

Quality investing is an old concept that continues to grow. With the growth of the Indian stock market, multiple investing styles need to be developed to cater to the varied risk profile of the investor. Smart beta index funds are recommended for moderate risk-averse investors seeking to contain downside risk in equities, offering lower charges and eliminating fund manager risk.

Quality stocks possess good fundamentals, which ensure that they will not only survive but also thrive. These stocks are expected to give returns in the long term. The lack of a clear definition to identify quality has led to the developing of multiple indicators such as profitability, solvency, earnings quality, and many more. These metrics have also propagated a race amongst academicians to identify the best indicators for different economies at different periods. Empirical academic evidence has failed to provide a clear pathway to a single metric that can assure returns. However, some essence from the empirical research has led to the creation of a framework for the development of indices. These indices allow the creation of ETFs, which attract more investor funds. Indian indices based on quality have shown promising potential for long-term investing.

Retail investors are taking over equity markets in India, driving a paradigm shift in the economy. In FY22, Indian families saw a 2.5x increase in mutual fund investments, with over 10 million new investors investing ₹1.2 trillion. Despite the US Fed's 4.25% rate hike and foreign institutional investors withdrawing from emerging markets like India, Indian markets have remained resilient, with the Nifty50 gaining 7.5% this year (Ravi Kumar, 2023).

Well-composed ETFs based on indices created from single-factor quality or multifactor will allow investors to choose the style that suits their needs. For a developing economy like India with a thriving capital market, quality investing can sustain capital market growth in the long term.

Annexure A: List of Quality Indices

Index	**Returns (%)**				**Beta**	**Benchmark**		**Launch Year**	**Quality Metrics**
	1yr	**3yr**	**5yr**	**YTD**	**YTD**	**Name**	**Return (%)**		
Nifty100 Quality 30	16.62	19.42	13.44	15.67	0.79	Nifty 100	17.06	2015	Return on Equity, Debt to Equity, Earnings growth variability
Nifty200 Quality 30	15.87	18.49	13.63	18.36	0.78	Nifty 200	14.18	2018	Return on Equity, Debt to Equity, Earnings growth

Index	Returns (%)				Beta	Benchmark		Launch Year	Quality Metrics
	1yr	3yr	5yr	YTD	YTD	Name	Return (%)		
									variability
Nifty Midcap150 Quality 50	13.88	20.07	14.95	19.00	0.68	Nifty Midcap 150	17.25	2019	Return on Equity, Debt to Equity, Earnings growth variability
Nifty Quality Low-Volatility 30	15.33	18.47	13.03	17.17	0.69	Nifty 100	17.06	2017	Return on Equity, Debt to Equity, Earnings growth variability
Nifty Alpha Quality Value Low-Volatility 30	29.24	25.15	17.22	17.71	0.72	Nifty 100	17.06	2017	Return on Equity, Debt to Equity, Earnings growth variability
MSCI ACWI Quality Index	28.73	6.97	9.93	7.74	0.90	MSCI ACWI	5.65	2012	Return on Equity, Debt to Equity, Earnings growth variability
MSCI World Quality	29.70	8.32	10.55	10.76	0.9	MSCI World	7.24	2012	Return on Equity, Debt to Equity,

Index	Returns (%)				Beta	Benchmark		Launch Year	Quality Metrics
	1yr	3yr	5yr	YTD	YTD	Name	Return (%)		
Index									Earnings growth variability
MSCI Emerging Markets Quality Tilt Index	13.02	-0.81	1.61	5.31	0.97	MSCI EM	4.7	2014	Return on Equity, Debt to Equity, Earnings growth variability
MSCI Europe Quality Index	21.78	5.05	7.43	9.27	0.82	MSCI Europe	6.51	2012	Return on Equity, Debt to Equity, Earnings growth variability
MSCI USA Sector Neutral Quality Index	28.80	10.03	9.74	8.03	0.95	MSCI USA	7.27	2014	Return on Equity, Debt to Equity, Earnings growth variability
BSE Quality Index	20.11	23.74	15.48	17.84	-	S&P BSE LargeMidCap	15.32	2015	Return on Equity, Debt to Equity, Accruals ratio
S&P 500 Quality Index	28.27	10.84	10.81	11.75	-	S&P 500	11.91	2014	Return on Equity, Debt to Equity,

Index	Returns (%)				Beta	Benchmark		Launch Year	Quality Metrics
	1yr	3yr	5yr	YTD	YTD	Name	Return (%)		
									Accruals ratio
S&P MidCap 400 Quality Index	30.97	15.63	11.80	12.42	-	S&P 400	8.94	2017	Return on Equity, Debt to Equity, Accruals ratio
S&P SmallCap 600 Quality Index	20.25	13.9	5.13	10.03	-	S&P 600	8.15	2017	Return on Equity, Debt to Equity, Accruals ratio

(Source: Author's working)

Note:

1. Data on beta is not available for S&P indices
2. For S&P indices, 10-year returns have been used as a substitute for YTD returns

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Chapter-4

MOMENTUM INVESTING: A RETROSPECTIVE REVIEW

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1. Introduction

Efficient Market Hypothesis (EMH) posits that investment strategies based on historical patterns cannot generate superior returns (Fama, 1970). However, (EMH) is confronted with several criticisms, primarily owing to various market anomalies, the most significant being Momentum. Momentum investment strategy emphasizes that buying past winners and selling past losers stocks generates superior returns in the next 3-12 months (Jegadeesh & Titman, 1993), contesting even the weak form of market efficiency. The persistence and prevalence of momentum returns have shifted the debate from momentum as an anomaly or an outcome of data mining to developing theories that can explain the success of momentum investment strategies (Joshipura & Wats, 2022). Fama and French (1996) explained that most return anomalies identified in the 1980s, such as size and value (Basu, 1977; Banz, 1981), could not explain medium-term momentum returns. Since then, momentum investment strategy has drawn substantial attention. Numerous studies have examined the factors of momentum returns in developed and developing markets, across asset classes, diverse periods, in various macroeconomic regimes, and different holding and look-back intervals. Several studies established that momentum strategy works across asset classes such as equity (Zhong, 2021), bonds (Polbennikov et al., 2021), commodities (Yan & Garcia, 2017), currency (Zhang, 2021), mutual funds (Wongchoti, 2013; Carhart, 1997), ETFs (Vanstone et al., 2021), futures (Guobužaitė & Teresienė, 2021), commodity futures (Bianchi et al., 2016; Jaiswal, 2021), green stocks (Chakrabarti & Sen, 2020), cryptocurrency (Liu et al., 2022) real estate (Hao, et al., 2016). Further, Asness et al. (2013) emphasize the pervasiveness of momentum investment strategy by constructing momentum strategies for equities in the US, UK, European equities, currencies, government bonds, and commodity futures.

This article is organized as follows: The second section illustrates the research trends in momentum investment strategy over the years, followed by factors driving momentum investment strategy. The fourth section presents the conclusion and provides future research directions.

2. Research Trends in Momentum Investment Strategy

2.1 Constructs of Momentum Investment Strategy

Several construct of momentum strategy that offers positive returns is the general cross-sectional momentum strategy by (Jegadeesh & Titman, 1993), which generates profits across all combinations of 3, 6, 9, and 12 months of formation and holding periods, followed by Blitz et al., (2011), residual momentum by adjusting raw returns to their risk-factor exposure that improves momentum profits. Further, Moskowitz et al., (2012) illustrate a time-series momentum strategy that proposes a pure bet on assets' return continuation instead of relative performance and claims to offer higher profits than a cross-sectional momentum strategy. However, Goyal and Jegadeesh (2018) contend that the superior performance of time-series momentum is owing to the high leverage effect. Novy-Marx (2012) illustrates momentum strategy by positioning a look-back period to an intermediate time horizon that claims to offer monthly profit returns of 1.20%. Moreover, Daniel and

Moskowitz (2016) demonstrate a construct by scaling proportionally to its conditional Sharpe ratio.

2.2 Empirical Demonstration of Momentum Investment Strategy

The seminal study by Fama and French (1992) reports the combined roles of market capitalization market beta, leverage, earnings multiple(E/P), and book-to-market equity (BE/ME) in explaining the market returns. Fama and French (1992, 1996) demonstrate that value stocks, including cash flow to price (C/P), high earnings to price (E/P), or book to market (B/M) outperforms stocks comprising of lower C/P, B/M, and E/P. Fama and French (1993) extend their 1992 study by considering bond markets and term structure to assess if factors are necessary for bond returns. Further, the authors also evaluate the stock returns, assuming that markets are integrated and co-related. The authors demonstrate that market factors like bond factors and market capitalization like default risk and maturity influence the returns of both bonds and stock.

Portfolio construction established on buying stocks that have performed well in the past and selling stocks that have performed poorly in the past generates significant returns throughout the three to twelve months' investment period (Jegadeesh & Titman, 1993). The long-term performance of the winners' and losers' portfolios discloses that half of their excess returns in the following year of portfolio construction dissipate within the forthcoming two years (Jegadeesh & Titman, 1993).

Rouwenhorst (1998) shows momentum returns across twelve countries and that international momentum markets are associated with the USA, which supports the idea that momentum profitability is determined by exposure to a conjoint factor. The author demonstrates that return continuation is negatively associated with firm size but not smaller firms. Hong et al. (2000) establish that analysts' coverage and firm size influence momentum returns. Okunev and White (2003) explore commodity futures and foreign exchange markets and confirm momentum returns. Korajczy and Sadka (2004) evaluate the impact of trading costs containing price impact on various momentum portfolio strategies, and trading costs models to estimate the momentum-based funds' size that may be attained before abnormal returns are statistically insignificant. The authors show that excess returns of some momentum investment strategies wane even if the initial investments are insignificant or otherwise, concluding that the price directions of trades and transaction costs do not illustrate the prevalence of returns of previous winners' stocks.

Erb and Harvey (2006) state that tactical strategies offer higher mean returns in the commodity futures market. Shen et al. (2007) illustrate that momentum returns in commodities futures markets are prominent for nine-month investment horizons, and the returns are similar in magnitude to stocks. The authors demonstrate that, although momentum investment strategies are risky, the market factor model cannot endorse such returns, and the returns are too high to be contained by the transaction costs. Liu and Zhang (2008) demonstrate that the combined impact of industrial production growth rate and risk premium explains the momentum returns. Hence, disapproving Jegadeesh and Titman's analysis of momentum returns due to behavioral underreaction of firm-related news. Menkhoff et al. (2012a) show momentum returns in foreign currency markets, confirm that they partly owe to transaction costs, and assert that they are due to under-reaction and not owing to conventional risk factors. Further, Menkhoff et al. (2012b) find robust momentum profits in currencies, which comprises of investing in the highest relative interest rate quantile portfolio and selling the lowest relative interest rate quintile portfolio. The authors confirm that standard risk measures cannot support these surplus returns. Fama and French (2012) extend their study on size, value, and momentum in international stock returns and confirm that the occurrence of value premiums moderates with size, with Japan being an exception.

Asness et al. (2013) confirm that momentum and value investment strategies offer significant returns across eight diverse markets and asset classes. The authors show strong co-movements of their returns across the asset classes and confront existing models for their presence. Lustig et al. (2014) demonstrate that countercyclical disparity in currency risk premium leads to high return probability and steers to high returns on the "dollar carry trade" strategy.

Moskowitz et al. (2012) apply a volatility scaling approach to avoid momentum crashes and enhance the return of momentum investment strategy. The authors establish that with less exposure to standard asset pricing factors, the time-series momentum investment strategies provide substantial abnormal returns across a well-diversified portfolio of worldwide futures contracts, which is more prominent in an up-trending market. Kim et al. (2016) demonstrate that assuming a buy-and-hold and time-series momentum offers the same cumulative return with similar alphas across the combined portfolio of futures contracts across various sectors. Moreover, the authors show that unscaled time-series momentum offers less alpha regarding cross-sectional momentum.

Further, to establish whether momentum is due to systematic risk or mispricing, a strand of literature examines momentum in portfolios that captures the factors related to individual stocks. Moskowitz and Grinblatt (1999) illustrate a positive return for a strategy sorting on past industry return owing to positive serial auto-covariance of industry factors. Furthermore, Ehsani and Linnainmaa (2022b), Gupta and Kelly (2019), and Arnott et al. (2021), illustrate momentum in factor returns to clarify the cross-section of stock returns owing to serial auto-covariances of risk factors. Ehsani and Linnainmaa (2022a) and Arnott et al. (2021) establish that factor momentum incorporates both industry momentum and stock momentum. Grobys and Kolari (2020) investigate industry momentum based on the ideas of Moskowitz and Grinblatt (1999) and suggest that there are several independent forms of industry momentum.

3. Factors Driving Momentum Returns

It is evident from the empirical demonstration that the momentum investment strategy offers positive returns. Two major argument strands, risk-based and behavioral aspects, try to describe momentum. The behavioral aspects illustrate that investors display certain types of biases that impact their trading actions and drive the stock price away from its underlying valuation. However, the risk-based argument states that the investor is rational and that momentum payoffs compensate for risks that arise from trading momentum.

3.1 Risk-Based Explanation for Momentum Investment Strategy

Risk-based explanations form momentum test probable momentum causes without leaving the sphere of rational investors' efficient market hypothesis (Fama,1970). Momentum returns are considered as compensation for taking crash, tail and liquidity risks. Risk-based models are more acceptable for the decade-long prevalence of momentum.

3.2 Behavioral Explanations

The behavioral theories on momentum investments presume serial correlation in individual stock returns directed by investors' biases and inability to discount the new information instantly and precisely.

Barberis et al. (1998) establish both under-reaction and over-reaction features for momentum, whereas Hong and Stein (1999) illustrated that under-reaction amongst investors results in momentum returns. Daniel et al., (1998) propose that short-term momentum and long-run reversals in stock markets are primarily due to overconfidence and self-attribution biases, causing prices to exaggerate. The authors establish that investors collect information and trade on stocks. Further, confirmation of public signals increases investors' overconfidence, escalating the price further. The occurrence of affirmative public information after the buy based on private information is attributed to investors' skill that escalates the price further. However, if public signal differs from investors' buying decision, such signals are rejected as noise. Nevertheless, as noise signals and subsequent public information arrive in the market, the stock prices attain correction and ultimately reach their precise valuation.

Jegadeesh and Titman (2001) approve that momentum returns cannot be endorsed to data snooping, thereby disproving Conrad and Kaul (1998) statement that momentum payoffs result from data snooping. The authors also endorse that underreaction and overreaction behavioral models might justify the persistence of momentum profits. Lee and Radhakrishna (2000) distinguish investor behavior from quote data and observed trade and recommend that observed trades' occurrence, size, and direction offer a realistic base for assessing the inward flow of market orders. This movement may offer necessary information about market direction and support to strategically design the portfolio, resulting in incremental returns. Chordia and Shivakumar (2002) establish that a set of lagged economic variables leads to momentum profits and deduce that momentum returns may be owing to time-varying expected returns. Johnson (2002) demonstrates that momentum profits may not be due to investors' irrationality, market friction, or heterogeneous information. It can be caused by using a single firm-pricing model with an unvarying kernel whose probable dividend growth rate deviates. Cooper et al. (2004) demonstrate that the success of momentum investment strategy depends on the market state and associate their findings with Daniel et al. (1998) hypothesis of investor overconfidence. Primarily, investors are long on equities, and owing to their self-attribution biases, an up-trending market situation will increase investor confidence, leading to higher overreactions and, thereby, momentum. However, the authors demonstrate a reversal of momentum profits in the long term.

Moreover, George and Hwang (2004) illustrate the presence of anchoring bias in explaining momentum, where investors' judgments are driven toward a specific reference point. The authors propose the 52-week high price as an anchor, as newspapers report it for all the stocks. The authors recommend that for stocks near their 52-week high, the new positive information is partly integrated into prices as traders are hesitant to cross over the anchor level. Grinblatt and Han (2005) suggest the disposition effect in investors that drives momentum in markets.

Further, Chui et al. (2010) support Daniel et al. (1998) and establish that momentum profitability in a country is positively connected to individualism, wherein average monthly momentum profits are 0.60% greater in countries that are positioned in the top 30% based on individualism than in countries that are positioned in the bottom 30%. The authors consider cross-country variations in overconfidence and self-attribution bias with Hofstede's (2001) individualism index, which the authors argue is positively related to these attributes.

Hong et al. (2000) demonstrate that smaller firms commonly drive momentum, and after adjusting for firm size, momentum performance improves when analyst coverage is low. Thus, the authors support Hong and Stein (1999) hypothesis that the preliminary underreaction to news is slow, owing to the gradual dispersal of information. Further, Zhang (2006) demonstrates that momentum impact heightens with information uncertainty. The authors show that the degree to which bad (good) news predicts low (high) future returns is greater for young and small firms, for firms with lower analyst coverage, for firms with higher cash flow uncertainty, for stocks with higher return uncertainty and with higher analyst forecast dispersal.

Novy-Marx (2012) shows that momentum is primarily driven by intermediate horizon past performance. In contrast, Antoniou et al. (2013) confirmed that investors' sentiments primarily drive momentum, and momentum profits arise only under optimism. The authors show that during good times, the bad news for loss-making stocks will disseminate very slowly compared to pessimistic times, resulting in negative returns for loser stocks. Moreover, the authors demonstrate that such an impact is more distinct when stark short-selling restrictions limit arbitrageurs' capability to drive down loss-making stocks to their intrinsic valuation.

Further, Hillert et al. (2014) confirm Daniel et al. (1998), overreaction theory by forming a firm-specific measure for excess media coverage that controls for stock index memberships, firm size, and analyst coverage. The authors claim that newspapers represent a basis for investors' private signals and demonstrate that monthly momentum returns are three times higher, 1.02% vs. 0.33%, on using the stocks subset in the maximum quintile of media reportage than while applying stocks in the lowermost quintile. Further, the authors establish evidence for Chui et al. (2010) and Daniel et al. (1998) by illustrating that the spread rises for stocks with high uncertainty, which is approved by overconfident investors and in extremely individualistic states. Moreover, Antoniou et al. (2013) establish that a 6-month momentum investment strategy offers an average monthly return of 2.00% when an investor's sentiment is high. However, the strategy offers only a 0.34% return when investor sentiment is low. Barroso and Santa-Clara (2015) find that momentum investment strategies provide the highest Sharpe ratio and confirm that managed momentum eliminates the crashes and doubles the Sharpe ratio. Daniel and Moskowitz (2016) state that the momentum strategy can experience intermittent and incessant negative values because of predictable momentum crashes in panic situations following market declines and high market volatility.

3.3 Returns of S&P 500 momentum index and BSE Sensex momentum index

The S&P 500 momentum index launched in November 2014, which aims to measure the performance of 100 securities in the S&P 500, has shown higher returns over longer time horizons than shorter periods. Even the BSE Sensex momentum index, launched in December 2015, has offered a higher annualized return rate than BSE Sensex performance. Hence, the higher returns of momentum index returns indicate momentum index strategy's pervasiveness and may be associated with data snooping and overreaction biases.

4. Conclusion

Momentum investment strategy as a research area gained impetus when it became evident that superior profits may be earned by buying past winners and selling past losers. Over the past three decades, several empirical and conceptual studies have illustrated the prevalence and existence of momentum investment strategies. Though momentum returns appear pervasive, they manifest differently in different asset classes and markets. This study aims to develop an in-depth understanding of the momentum investing strategy, construct the findings of the empirical studies, demonstrate the factors driving momentum returns, and propose prospective research directions. Over the years' momentum investment strategy has progressed from finding the returns with various holdings periods, reversal, return predictableness, abnormal returns, and profitability to market states. Post-2015, the focus shifted to real estate, time-series momentum, commodity futures, mispricing, momentum crashes, and investor sentiments to portfolio construction, momentum crashes, term structure, and portfolio performance measurement in 2020. Several empirical and theoretical studies have been undertaken, but the results demonstrate mixed results. Though both behavioral and risk-based models offer judicious reasons for firm-specific momentum, the new strands of literature that illustrate the existence of industry and factor momentum do not provide theoretical foundations. Hence, future studies can examine the theoretical models for the existence of industry and factor momentum. Further, the researchers can observe the momentum in the new asset classes and illustrate the drivers against such outcomes.

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Chapter-5

LOW VOLATILITY INVESTING

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1. Introduction

What is the risk Anomaly?

Conventional finance theories, such as the Capital Asset Pricing Model (CAPM) (Sharpe, 1964) and Modern Portfolio Theory (MPT) (Markowitz, 1952), envisage a positive relationship between systematic risk and the stock's expected return. According to modern portfolio theory, investors should earn rewards for taking the idiosyncratic risk as it is fully diversifiable. CAPM uses beta to measure systematic risk and offers a model that depicts a positive linear relationship between expected return and risk. However, with the increased availability of data and enhanced computing powers, the early studies on CAPM revealed that the relationship between the risk and return is flatter than expected. The low-risk stocks deliver superior risk-adjusted returns compared to their high-risk counterparts and market portfolios. It was attributed to borrowing constraints. Some studies even claimed a negative relationship between risk and return. Early evidence of such an anomalous relationship was discarded as an outcome of data mining or an anomaly that should disappear. However, it persisted over a long period and was robust to the choice of risk measures, such as standard deviation, beta, or idiosyncratic risk, across developed and emerging markets. It remained strong across different lookback and holding periods. Such persistence of relationship led to the debate on explaining such relationship. While other factors such as value, size, and momentum have risk-based and behavioral arguments, the persistence of low-risk anomaly is difficult to explain by conventional finance theories.

Multiple economic and behavioral theoretical explanations have emerged that explain the persistence of low-risk anomaly. Some other propositions offered theoretical reasons that refuted the very existence of such an effect.

2. What explains risk anomaly?

2.1 Borrowing and Leverage Constraints

As early as the 1970s, Black (1972) reported a flatter-than-expected relationship between risk and return, recognizing short selling and borrowing restrictions as explanations for such a relationship to persist. It results in stocks with low beta offering positive alpha and stocks with high beta offering negative alpha. Baker et al.(2011) extended the explanation, claiming that the pressure to beat the benchmark for long-only equity fund managers combined with myopic investor preferences forced fund managers to choose stocks with high beta despite their negative alpha.

For example, if a fund manager has two portfolio choices in front of her,
Portfolio X: Beta = 0.8 and Alpha = 1%
Portfolio Y: Beta = 1.2 and Alpha = -1%.

If the benchmark index gains 10% for the year, portfolio X will deliver an 8% return, whereas portfolio Y will provide a 12% return. Hence, if investors focus only on absolute performance rather than risk-adjusted performance, they will consider portfolio Y as a superior return-yielding investment opportunity, and the fund managers who have chosen portfolio X might end up seeing investors exiting their fund. Yes, as the market goes down, the actual worth of Portfolio X becomes visible, but investors with myopic views cannot see that. Even the fact that, on average for each down-year, equity markets have four up-years makes it highly challenging for fund managers to opt for portfolio X despite being a superior portfolio.

Suppose the borrowing is allowed to create a levered portfolio to generate higher returns from the low-risk portfolio. In that case, investors in portfolio X can add financing risk to portfolio X. They can lever up the beta to match the market beta of one or even push the beta to match the beta of portfolio Y, which is 1.2. However, in most countries, pension and mutual fund managers face long-term borrowing constraints and hence fail to exploit the low beta-positive alpha opportunity and end up pushing demand for high beta-negative alpha stocks. Such benchmark-beating mandates combined with advantage constraints eventually lead to high-beta stocks being overpriced and low-beta stocks being underpriced, resulting in the eventual outperformance of low-beta stocks and the underperformance of high-beta stocks on a risk-adjusted basis. Low-beta stocks continue to enjoy positive alpha since such an opportunity becomes challenging to arbitrage away.

High beta stocks have negative alpha, making the actual relationship between stock return and beta flatter than the one envisaged by CAPM.

CAPM and its variants are typically single-period models. They provide a framework to compute ex-ante expected returns for a stock based on the systematic risk measured by beta for one period. However, in practice, investors make investment decisions with a multi-year horizon. Hence, the relevant measure of return is compounded return rather than simple annual return. A single-period return and the variance of such returns drive the compounded return.

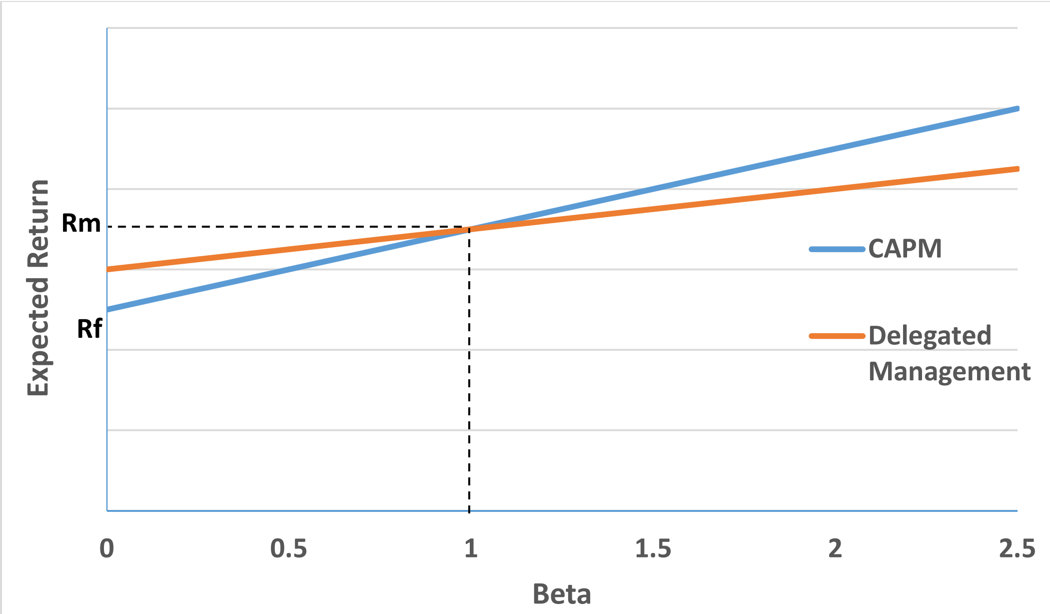

Figure 1: Expected vs. actual security market line

The following equation describes the relationship between simple and compounded returns.

Geometric mean or CAGR = $\mu - 0.5 * \sigma^2$ Equation 1

Where μ is the simple arithmetic mean of annual returns, and σ^2 is the variance of annual returns.

This means that the CAGR or geometric mean and simple annual return are the same for only risk-free assets. For any risky asset, there is variance drag (2nd term in Equation 1), which brings down the CAGR of such investments.

It implies that if there are two stocks with the same expected returns, but one with higher volatility than the other, in the end, the stock with lower volatility will deliver higher compounded returns.

For example, stocks A and B have identical annual expected returns of 14%, but stock A's volatility of annual returns is 15%, whereas the corresponding volatility for stock B is 30%. Therefore, over time, stock A will deliver a CAGR of 12.875%, whereas stock B will provide a CAGR of 9.5%. For investors with long-term investment horizons, the stock with lower volatility and lower drawdowns will generate superior CAGR for comparable opportunities with similar expected returns. The following table explains how large drawdowns result in significant wealth erosion and take much longer to break even.

Table 1: Winning by losing less.

Percentage Drawdown	Returns required in the next period to Break even
10%	11%
20%	25%
25%	33%
33%	50%
40%	60%
50%	100%
75%	300%
90%	900%

Looking at Table 1, it is evident that long-term investing is all about winning by losing less. Given the evidence of poor timing skills of individual and institutional investors, it always helps to hold stocks that face lower drawdown given everything else. It is true at both the stock or portfolio and market levels.

Emerging markets like India can deliver superior returns than developed markets like the USA due to their higher economic growth potential than developed nations. However, comparing equity market returns of these markets offers exciting insights.

Table 2: US vs Indian markets performance (1991-2008)

Particulars	Dollex-30	DJIA
Simple Average Annual Return	13.5%	9.5%
CAGR	8.16%	8.1%
Annual Volatility (Standard Deviation)	35.39%	15.02%
Best return year (2009)	87.87%	33.45%
Worst return year (2008)	-61.41%	-33.84%

Source: Authors calculations based on Bloomberg and bseindia.com data

Table 2 compares the performance of two indices: a dollar-denominated version of India's oldest stock market index, BSE Sensex, Dollex-30, which comprises 30 stocks, and one of the oldest US market indices, DJIA 30, which also contains 30 stocks. Table 2 shows that the annual average return for Dollex-30 for the 28 years from 1991 to 2018 was nearly 13%, much higher than the corresponding return for DJIA, 9.5%. Meanwhile, the CAGR for both Dollex-30 and DJIA was similar and close to 8.1%. In fact, given that DJIA has a higher dividend yield than Dollex-30, the total dollar return on the DJIA index is higher than that of Dollex-30. It appears surprising, but it is not. Given that Dolelx-30's annualized volatility was 35% compared to DJIA's 15%, Dollex-30 witnessed large and frequent drawdowns, creating a much higher variance drag on its long-term returns than DJIA.

For example, if an investor had invested $100 in DJIA at the end of 2007, by the end of 2009, the investment in DJIA would have been worth nearly $88, a 12% erosion in the capital. In contrast, the same investment in Dollex-30 for the same period would have been worth close to $72.5, with 27.5% capital erosion from initial investment at the end of 2007. However, Dellex-30 delivered a massive 87.73% return in 2009, whereas DJIA delivered mere 33.45%. However, what happened in 2008 had a more significant impact on the returns of the two markets. Although the global financial crisis of 2008 had its origins in the USA, India remained largely insulated from the crisis.

Given that India is a more volatile market, it lost 61% of its value in 2008, a negative 1.7% standard deviation event. DJIA lost 33%, which is close to two standard deviations event. So, while both markets saw nearly 2 standard deviations negative returns in 2008, given the low volatility of US markets, the drawdown was much smaller, resulting in a faster recovery in 2009. Despite the Indian equity market recording the best year in history regarding dollar returns in 2009, it failed to beat the US market. It implies that losing less in the bear market is the real success of long-term investing and a crucial factor that drives the risk anomaly. If someone knows the perfect market timing, one should have exited US markets and entered Indian markets at the end of 2008. Still, such an attempt to time the market within and across asset classes has resulted in average performance-chasing behavior and negative timing alpha. So, low-volatility investing makes a prudent investment for someone with a long-term investment horizon and imperfect timing skills.

2.2 Fund Manager's Compensation Structure

Fund managers of managed funds such as hedge funds and Portfolio Management Services (PMS) in India have a two-part compensation structure: fixed asset management fees and a performance fee, typically above a threshold return. For example, "1 and 20' means the fund charges a fixed fee of 1% annually and will share 20% of profit once a predetermined threshold return is achieved (e.g., 10% or 12%). Of course, there are high watermark provisions. So, the fund managers cannot claim the performance fee if the compounded return or internal rate of return does not meet the hurdle rate. However, investors have a myopic view. They look at the short-term performance combined with the fact that the fund managers' performance is evaluated every year and the tendency of fund houses to close down the fund, which is unlikely to meet the high watermark after a series of poor annual returns. Together, these result in fund managers opting for portfolios with higher volatility.

Therefore, such a call-option-like fund manager's compensation structure will lead a fund manager to choose a portfolio with higher volatility of return distribution even if it has lower expected returns than a portfolio with lower volatility and higher expected returns (Figure 2).

No wonder, with a mandate to outperform the benchmark and PMS and hedge fund managers with call option-like compensation structures, long-only mutual fund and pension fund managers might prefer high beta (despite negative alpha) and high volatility (despite lower expected returns) stocks and portfolios. Such systematic preference for high beta and high volatility stocks results in the eventual under-pricing of low beta and low volatility stocks that would drive their outperformance in subsequent periods.

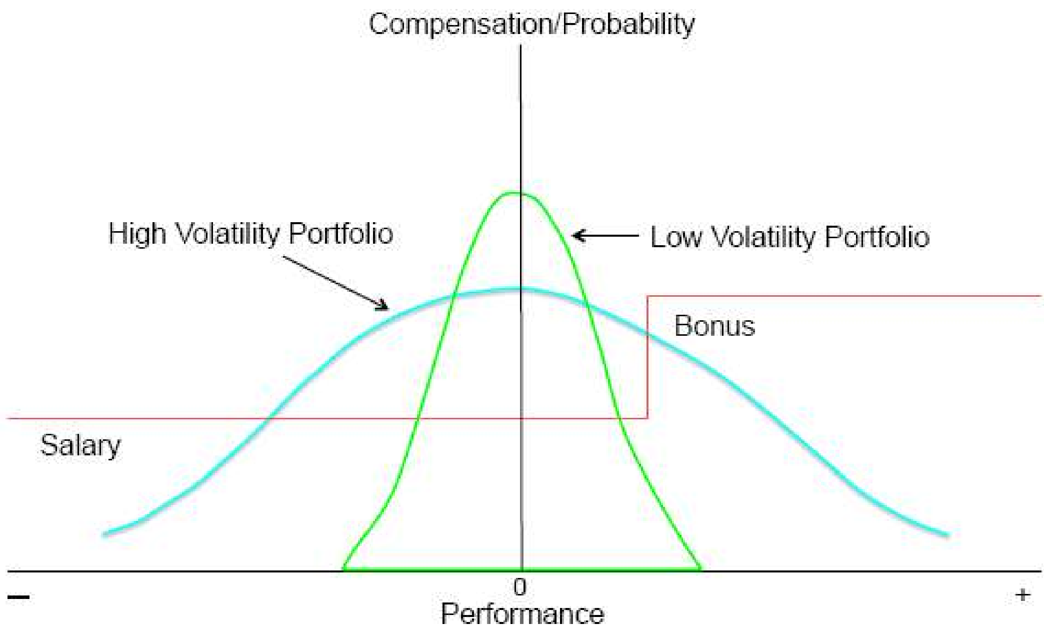

Figure 2: Fund managers' compensation and portfolio choice

2.3 Preference for Lottery-like Payoffs

Why any rational individual would purchase a lottery has remained a long-standing puzzle in economics for a long time. A lottery buyer faces a negative expected return with a small probability of winning a jackpot or a big prize. The prospect theory explains it through its probability weighing function. According to prospect theory, individuals tend to overweight tail events' probabilities. This means an individual assigns a higher probability to a nearly improbable outcome like winning the lottery. For example, if one purchases a lottery for $50 with a jackpot of $1 million and the lottery seller has sold 100,000 such tickets. In this case, the probability of winning a jackpot for a lottery buyer is 0.00001, and the expected payoff is $10. If one purchases a lottery ticket for $50, the expected value is negative $40; hence, no rational individual should buy a lottery ticket.

However, one out of 100,000 lottery buyers would win the jackpot, and all buyers assign a higher probability than 0.00001 to their winning the lottery. Let us say one assigns a 0.0001 probability of winning the lottery. The expected payoff jumps to $100, and this overestimation of actual probability drives people to purchase lottery tickets. Small, penny stocks of distressed firms possess characteristics of a lottery. Such stocks are most likely to disappear from the scene and have zero value with a tiny probability of turnaround, which can lead to a multi-fold return. Such stocks attract the attention of investors searching for a 'get rich quick' recipe and end up pushing prices of such penny stocks even further, leading to poor returns in the future. Therefore, the skewed return distribution with a long right tail makes investors pay a premium for chasing such an unlikely outcome.

Bali & Cakici (2008) and Bali et al. (2011) claim that such risk anomaly is caused by the poor returns delivered by illiquid penny stocks. Hence, the risk anomaly should disappear if one removes such stocks from the stock universe. However, using the universe of stocks excluding illiquid and penny stocks, Joshipura & Joshipura (2016) and Joshipura & Joshipura (2020) show that the risk anomaly persists in the Indian stock market. Hence, it cannot be attributed entirely to the overpriced, illiquid, penny stocks with lottery-like payoffs.

Overconfidence, delegated fund management, and representativeness are the other theoretical explanations for the persistence of the risk anomaly.

3. Exploiting Risk Anomaly

However, exploiting and implementing such patterns remains challenging, like any other smart beta investment strategy.

The first hurdle is all factors typically developed as market-neutral long-short strategies, so is the case with betting against beta (BAB). The long and short legs of the portfolio contribute to the return of such investment strategies. Short-selling restrictions or security lending and borrowing markets have yet to be fully developed in several emerging markets. Besides, shorting stocks for an extended period comes with borrowing costs. Long-only investors miss the returns generated by the short leg of the factor. Hence, any smart beta investment strategy relies on the potential of the long leg of the strategy to deliver benchmark-beating returns.

While long-only low-volatility investment strategies look passive based on nature, but they still require many active choices, as listed below.

- Risk measure: Beta, Total volatility, idiosyncratic volatility.
- Period: Lookback period and rebalancing frequency
- Portfolio Construction method: Minimum Variance Portfolio vs. Ranking-based Low Volatility portfolio
- Portfolio Weighing Scheme: Value weighted, equal weighted, inverse of volatility weighted.
- Market focus: Country, Region, World

Several index providers have launched low volatility and minimum variance indices focusing on global, regional, and country-specific markets to exploit risk anomalies. Subsequently, several index and exchange-traded funds (ETFs) have been launched to track such indices and implement long-only investment strategies using low-risk anomaly for earning higher risk-adjusted returns over the return of benchmark market cap-weighted index.

Table 3 lists some ETFs that provide opportunities to invest in strategies that exploit risk anomalies. One can see the wide variety of ETFs trying to use the same strategy from different asset management companies. They could be different in many ways including their portfolio construction approaches (iShares MSCI USA Min Vol Factor ETF vs. Invesco S&P 500 Low Volatility ETF), market focus (iShares MSCI EAFE Min Vol Factor ETF vs. iShares MSCI Emerging Markets Min Vol Factor ETF), market capitalization buckets (Invesco S&P MidCap Low Volatility ETF vs. iShares MSCI USA Small-Cap Min Vol Factor ETF vs. SPDR SSGA US Large Cap Low Volatility Index ETF) and others trying to enhance attractiveness of low volatility investment strategy by combining it with other factors (Invesco S&P 500® High Dividend Low Volatility ETF).

Table 3: ETFs tracking low volatility or minimum variance indices and their variants (AUM > $500 million)

Symbol	ETF Name	Asset Class	Total Assets ($MM)
USMV	iShares MSCI USA Min Vol Factor ETF	Equity	$28,144
SPLV	Invesco S&P 500® Low Volatility ETF	Equity	$8,277
EFAV	iShares MSCI EAFE Min Vol Factor ETF	Equity	$7,202
EEMV	iShares MSCI Emerging Markets Min Vol Factor ETF	Equity	$4,297
ACWV	iShares MSCI Global Min Vol Factor ETF	Equity	$4,196
SPHD	Invesco S&P 500® High Dividend Low Volatility ETF	Equity	$2,881
LVHD	Franklin U.S. Low Volatility High Dividend Index ETF	Equity	$846
XMLV	Invesco S&P MidCap Low Volatility ETF	Equity	$845
SMMV	iShares MSCI USA Small-Cap Min Vol Factor ETF	Equity	$822
LGLV	SPDR SSGA US Large Cap Low Volatility Index ETF	Equity	$784
GLOV	Goldman Sachs ActiveBeta World Low Vol Plus Equity ETF	Equity	$740
EELV	Invesco S&P Emerging Markets Low Volatility ETF	Equity	$737
FDLO	Fidelity Low Volatility Factor ETF	Equity	$712
LVHI	Franklin International Low Volatility High Dividend Index ETF	Equity	$634
ONEV	SPDR Russell 1000 Low Volatility Focus ETF	Equity	$556
IDLV	Invesco S&P International Developed Low Volatility ETF	Equity	$528

4. Performance of Low-volatility Investment Strategy

The performance of low-volatility investment strategies has been a mixed bag. It performed on expected lines over the years. Still, since the global equity market crash of March 2020, most global markets witnessed significant outperformance of small cap, value, and cyclical commodity stocks and significant underperformance of low-risk and quality stocks. While the low-volatility investment strategy saw smaller drawdowns and lower volatility over different investment horizons and outperformed markets during stressed times, recent outperformance of low-risk, quality stocks in global markets over the last three and a half years has resulted in significant underperformance of low-volatility indices in developed markets such as USA over their broad-based benchmark index S&P 500. However, in emerging markets like India, the low-volatility ETFs have outperformed broader markets on an absolute and risk-adjusted basis over different horizons.

Table 4 shows the performance of the Low volatility index in Indian and US markets.

The S&P 500 low volatility index selects the 100 least volatile stocks from the constituents of the S&P 500 index and applies inverse volatility weighing for index construction. S&P BSE Low Volatility 30 index contains the 30 least volatile stocks selected from the largest 300 stocks listed at BSE and uses inverse volatility weighing for index construction.

Table 4: Annualized return and risk of market index vs Low volatility indices in US markets (As of October 31, 2023)

	Panel A: Annualized Total Returns			
	1 Year	**3 Year**	**5 Year**	**10 Year**
S&P 500 Low Volatility Index	-2.84%	6.34%	6.54%	8.65%
S&P 500	10.14%	10.36%	11.21%	11.18%
	Panel B: Annualized risk measured by standard deviation			
S&P 500 Low Volatility Index		14.37%	15.34%	12.34%
S&P 500		17.81%	18.69%	14.95%

Table 4 shows that in US markets, the low volatility index has underperformed the S&P 500 over one, three, five, and ten-year periods and by a substantial margin. However, long-term underperformance is the highest for the five-year CAGR, where the underperformance over the S&P 500 is massive at 4.67%. As discussed earlier, such significant outperformance can be explained by the strong performance of small, value, and cyclical stocks over the past three and a half years. However, the difference in CAGR is about 2.5% over ten years, which means five years between November 2014 and October 2019. The risk of the Low volatility index is consistently lower for three, five, and ten-year periods. Even with the long-term (beyond ten years) superior performance of low volatility investment strategy, such a prolonged period of underperformance tests the patience of even long-term investors. It makes it challenging to stick to such an investment strategy. Besides, for professional money managers, such prolonged periods of underperformance and significant tracking errors might pause serious career risk.

T able 4: Annualized return and risk of market index vs. Low volatility indices in Indian markets (As of October 31, 2023)

	Panel A: Annualized Returns			
Total Return Index	1 Year	3 Year	5 Year	10 Year
S&P BSE Low Volatility Index	16.27	17.11	15.27	16.50
S&P BSE Sensex	6.54	18.67	14.51	13.13
	Panel B: Annualized risk measured by standard deviation			
S&P BSE Low Volatility Index		12.14%	13.46%	12.92%
S&P BSE Sensex		14.51%	18.50%	16.19%

The story of the Indian equity market is different. Since the last decade, the Indian market has behaved more like US markets, with three-, five, and ten-year volatility similar to developed markets like the US. Besides, just like the US markets, India's low-volatility index volatility is consistently lower than the Sensex. However, when it comes to return, the story is different. Except for three-year returns, the LV index outperformed Sensex on one-year, five-year, and ten-year returns. So, while there was also a significant high beta, cyclical, value stocks rally in India, it turned around in favor of low volatility stocks in the last year.

5. Conclusion

Risk anomaly offers an opportunity to follow a long-only smart beta investment strategy to have a portfolio tilted toward low-beta stocks with the potential to outperform the market on an absolute return and a risk-adjusted return basis over the long term. However, it remains a difficult strategy to stick with due to the long periods of underperformance and significant tracking errors. It is challenging for individual and institutional investors and third-party money managers to follow such a strategy. As we conclude, one clear thing is that low-volatility investing is all about "winning by losing less."

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Chapter-6

ESG INVESTING

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Introduction

ESG investing involves considering environmental impact (E), social impact (S), and quality of governance (G) of assets in constructing and managing investment portfolios. ESG investors differ in terms of what motivates them to invest in ESG. ESG ratings diverge between rating providers. The theory behind ESG as a factor is still evolving, and many still question returns to ESG. Despite these challenges, ESG investing is a fast-growing theme under various investing methods.

The first section of this chapter provides an understanding of ESG investing, including investment methods. The second section explains ESG investing in practice, including used cases. The third section discusses the rationale for treating ESG as a factor and the evidence of its performance. The fourth section discusses the implications, and the fifth section concludes.

1. Understanding ESG Investing

ESG investing refers to incorporating environmental, social and governance considerations while investing. However, this broad term has different meanings that vary across investors and contexts. In public markets, for instance, ESG strategies are more likely to target the return-risk profile to mitigate ESG risks or benefit from favourable ESG-related opportunities. In private markets, on the other hand, sustainable investing strategies are more likely to focus on impacting societal outcomes while earning financial returns.

Though investing with non-pecuniary considerations has a long history, in a formal sense, sustainable investing started with Socially Responsible Investing (SRI) funds. SRI, in its original form, was based on the personal values or preferences of investors. An SRI fund would target investors with a similar set of views or preferences. The primary investment strategy used was the negative screening of 'sin stocks', meaning that stocks of certain businesses, such as tobacco or weapons, would be excluded from the portfolios.

Though not explicitly communicated to investors, this implied a potential sacrifice of returns since the investment opportunity set gets reduced due to the exclusionary constraints. Negative screening, being a simple strategy, also tends to be transparent, leaving little scope for compromise with investor preferences or values. Over time, SRI incorporated other methods, such as positive screening, impact investing and best-in-class investing.

ESG investing became popular in the 2010s with improved measures and indicators of E, S, and G. Several ESG data providers and rating agencies supplied information to support sustainable investing less subjectively. Index providers, using proprietary or third-party ESG ratings, launched ESG indices. ESG indices not only provided a benchmark for responsible funds, but they also aimed to provide evidence regarding the effect of sustainable investing choices on the return-risk profile of portfolios. Further, they would spur the development of passive ESG investing through ESG exchange-traded funds (ETFs) and ESG index funds based on such indices.

The advent of ESG investing had at least three consequences for sustainable investing – on the scope, objective, and scale. Regarding scope, ESG brought the governance pillar to sustainable investing since, in the traditional SRI concept, governance only refers to oversight of responsible investing commitments. In comparison, G in ESG largely follows agency theory-based constructs such as board structure and diversity, with the intent to ensure accountability of the management to the shareholders. However, there is usually some weight assigned to stakeholder relationships as well. The relative importance of E and S also effectively changed, as the focus of exclusionary SRI investing or impact investing tended to emphasise social aspects, the environment being one of the several targeted societal outcome areas. With ESG, the environment gained more weight, and the emerging scientific and political consensus on climate urgency took centre stage.

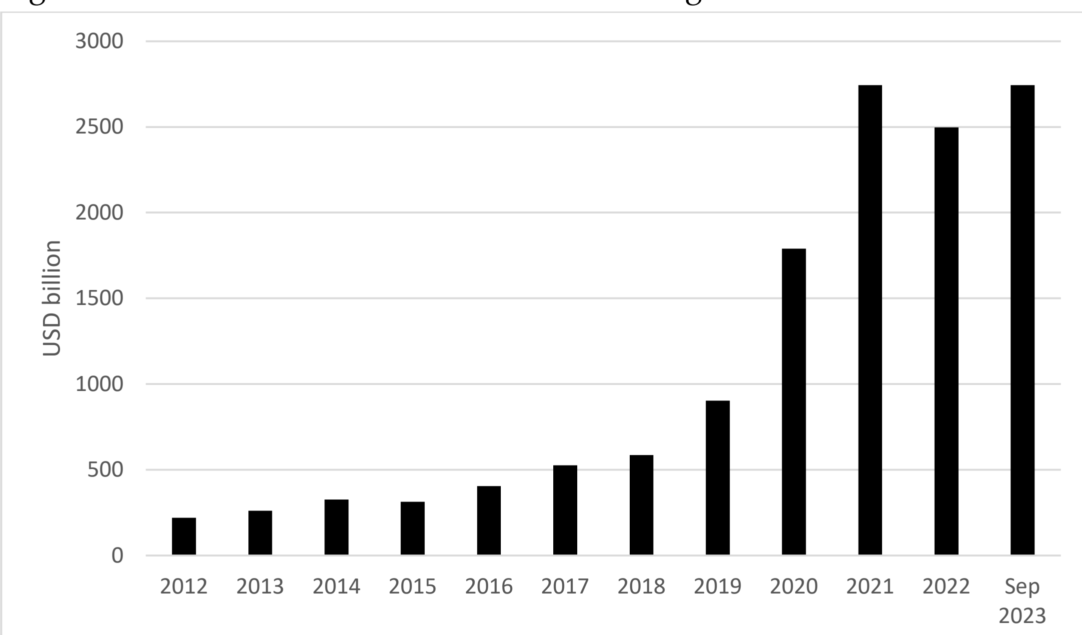
In terms of objectives, ESG investing became increasingly divorced from impact investing – in ESG investing, the emphasis is on financial returns, not, unless explicitly stated, on societal outcomes. E, S & G considerations are "inputs" to ensure that the risks and opportunities affecting the firm's value get comprehensively evaluated. Some commentators refer to this as "value-orientation" as distinct from the "values-orientation" of traditional impact investing and even the conventional SRI.

Further, in ESG investing, stocks are not painted in black or white; they differ in their ESG attributes on a spectrum. Even though ESG rating agencies provide scores that rank the firms, the divergence of ratings among agencies, the dynamism in ratings of firms, and the different rating attributes make the rating data malleable. As the incorporation of sustainability in investing becomes more data-driven and statistical, it is conceivable that an investor may not intuitively understand from an ESG fund's holdings how the weights of the stocks get aligned with "values" or even societal outcomes.

Finally, the easily quantifiable methods, less focus on personal preferences, and the stated or implied absence of trade-offs with financial returns have enabled ESG investing to scale up significantly. If financial returns are not sacrificed, it becomes easier for institutional investors to justify ESG investing since there is no conflict with fiduciary duty. Retail investors can get attracted to the promise of attractive financial returns, with no requirement to have common shared values. Some proponents believe that the traction in retail is also due to the higher sensitivity of the millennials towards sustainability issues. It is not surprising, therefore, that ESG investing has become the dominant label in sustainable equity investing, relegating the SRI label to the sidelines. Impact investing is now reserved mainly for the private investing space.

According to Morningstar, the total assets held by sustainable funds globally amounted to $2.7 trillion at the end of September 2023 (Morningstar, October 2023), recovering after falling from the peak of $3 trillion at the end of 2021 to around $2.3 trillion by September 2022 (see Figure 1). Regarding long-term comparisons, sustainable assets have grown nearly fivefold from about $585 billion at the end of 2018 and more than tenfold from around $262 billion at the end of 2013 (UNCTAD, 2023). Morningstar's definition includes open-end funds and ETFs and considers intentionality rather than holdings. These figures should be reasonably representative of the size of ESG investment funds. While the statistics may not be comparable to those reported by other sources due to the basis of reporting, the high-growth trend is likely to be universal.

Figure 1. Global Sustainable Assets Under Management



Source: Compiled by author from Morningstar, UNCTAD

ESG investing, as prevalent today, follows the strategies listed below.

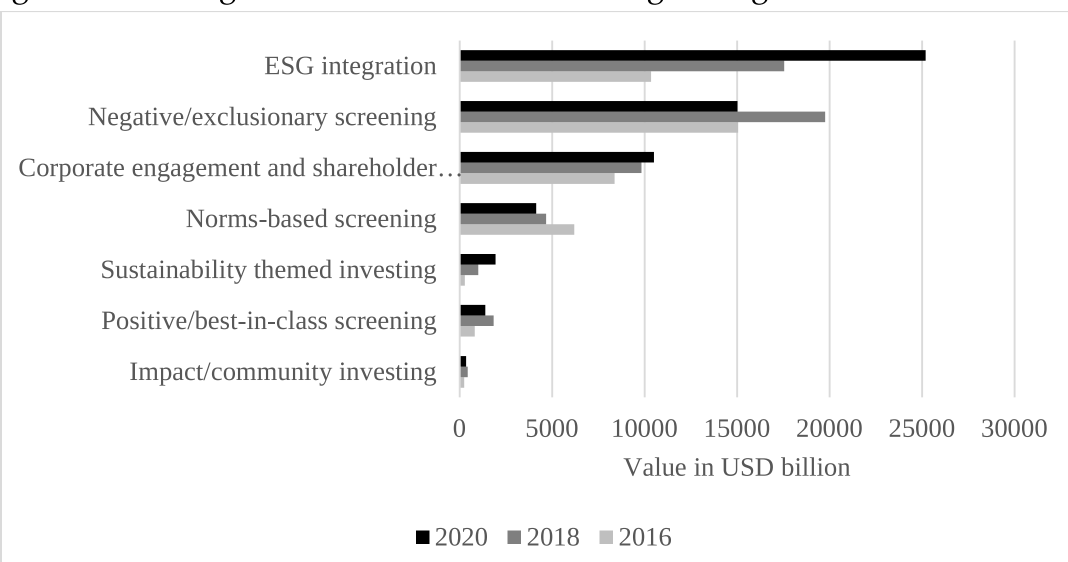
Screening: Screening involves applying a filter to the opportunity set of investments to select those that best represent the investors' ESG preferences or mandates. There are three forms of ESG screening – negative, norms-based and best-in-class (also called positive).

ESG integration: ESG integration involves considering ESG factors in investment analysis and portfolio decisions aimed at managing the risks or improving the returns.

Thematic investing: Thematic investing involves identifying securities of issuers whose activity covers specific areas of sustainable development.

Figure 2 shows the growth of ESG investing by strategy, as per the classification by the Global Sustainable Investment Alliance (2021). By 2020, ESG integration had become the most significant investing strategy by asset value, having overtaken negative screening.

Figure 2. Global growth of sustainable investing strategies 2016-2020



Source: Global Sustainable Investment Review 2020, https://www.gsi-alliance.org/wp-content/uploads/2021/08/GSIR-20201.pdf

In the context of factor investing, ESG integration is the most relevant investing strategy. Hence, in the remaining part of this article, ESG factor investing will refer to ESG integration strategy only.

2. ESG Factor Investing in Practice

2.1 ESG Investment Information Infrastructure

ESG investment rests on the foundation of its information infrastructure. It is essential to appreciate that developing a solid information infrastructure is crucial to the success of ESG as a driver of investment returns and risks. We can describe the information infrastructure in six information levels in Figure 3 below.

Figure 3. ESG information levels

Level 6	ESG Indices
Level 5	ESG Ratings
Level 4	Data Aggregators
Level 3	Company Disclosures + Independent Data
Level 2	Standards
Level 1	Definitions

Source: Author

At Level 1 are definitions, and it will be unwise to take these for granted. Though within ESG, one would expect more similarity in definitions of E, S and G, the same need not be true.

Take G, for instance. G is often derived from the traditional understanding of corporate governance, which has its roots in the shareholder-centric agency theory. However, in the ESG context, other stakeholders are also crucial from a sustainability perspective. This broadening of perspective makes it difficult to arrive at a unified definition. We end up understanding and, hence, measuring G through its components rather than as an integrated, meaningful construct. S also faces an issue of commonality of understanding. Though the relevant U.N. SDGs provide a common reference point, there can be significant variation in interpretation due to both variations across cultures and disagreements on viewpoints. E may be the least controversial component, but there can be narrow definitions almost entirely focussed on climate risks, and broader definitions encompass various environmental risks, including climate risks.

Further aggravating the problem of non-uniformity, these definitions are often provided by data aggregators or ESG rating providers, which, being commercially competing entities, have greater interest in differentiation than in standardisation.

Sustainability standards at Level 2 have more significant potential for convergence due to the involvement of global standard-setting bodies. Indeed, there has been much progress facilitated by consolidation among standard-setters and active efforts towards convergence. Two dominant standard-setting bodies today – IFRS and GRI have taken steps towards aligning their standards. Convergence is still held back due to fundamental disagreements on perspectives. From one perspective, material sustainability issues must be identified based on financial risks. According to the other (more favoured in Europe), double materiality is crucial; both financial risks and sustainable impact outcomes are essential.

The use of these standards in company reporting (Level 3) varies by country, depending upon regulation. While some countries have adopted global standards such as SASB (consolidated with IFRS) and GRI, others have their own standards. More crucially, there are regional differences in coverage of companies that are required to disclose non-financial information and the extent to which they have to disclose.

Apart from information disclosed by companies in their filings, independent data providers capture information either directly from the companies or alternative sources. Data aggregators (Level 4) such as Bloomberg and Refinitiv collect and structure the ESG information as per their proprietary

ESG frameworks. Since ESG disclosures have been scarce, unregulated and non-standard historically, the history and extensiveness of ESG data is limited compared to financial data inputs for investment.

ESG ratings (Level 5) form the heart of the ESG information infrastructure. They inform the decision of where to invest and in what proportion. Third-party evaluation distinguishes ESG investing from impact investing and traditional values-based SRI. The rating framework of an ESG rating agency defines the scope of the assessment, usually in terms of the subcomponents of E, S and G pillars, how materiality is assessed and translated into weights of the subcomponents, the proxy indicators for each subcomponent, and how each firm is scored on each proxy indicator given the disclosed information (or lack of it).

Rating agencies can differ in terms of the method, scope, the proxy indicators used, and the weights given to the indicators. In terms of process, too, they may differ in terms of the extent of analyst intervention versus automation of the rating process. These differences, aggravated by industry fragmentation, have resulted in significant variations in ESG ratings. Some have expressed the hope that the convergence of ESG reporting standards and some regulatory intervention will enable the alignment of ratings. However, the intrinsic problems of subjectivity and differences in perspectives in defining ESG components, particularly for the S and G pillars, remain sticky. Well-known ESG rating providers include Sustainalytics (owned by Morningstar), MSCI, ISS ESG, Refinitiv (owned by LSEG), Bloomberg, S&P Global and V.E. (part of Moody's ESG Solutions).

ESG indices (Level 6) bridge ESG ratings and ESG funds. They provide the benchmarks for ESG funds. When investible, they can be used to create ESG ETFs and ESG index funds. They can provide the universe for stock selection by active managers. Given that academic literature has yet to endorse ESG investing as a valid return-generating strategy, the performance of ESG indices plays an essential role in making a case for (or against) ESG investing.

Major ESG indices can encourage companies to improve their practices and disclosure to remain or become constituents. However, critics can argue that it may encourage companies to greenwash to boost their ESG ratings.

There are many ESG indices across asset classes, and they differ based on underlying definitions and ESG ratings. Some of the leading providers of ESG indices include MSCI, Bloomberg and S&P Global Dow Jones.

2.2 Construction of ESG Investment Strategies

As discussed earlier, ESG screening, ESG integration and Thematic investing are three broad ESG investment strategies. Table 1 summarises the approach to portfolio construction for sub-categories of ESG screening and ESG integration. Thematic investing is closer in scope to impact investing and is not discussed here.

Table 1. Construction of ESG Investment Strategies

Strategy	**Definition**	**Approaches/ Steps**
Screening	Applying filters	
negative/ exclusion	to rule out companies based on investor's preferences, values or ethics	a. Avoiding specific activities (such as: alcohol, tobacco, gambling, adult entertainment, military weapons, fossil fuels, nuclear energy). b. Avoiding worst-in-class companies.
norms-based	excluding companies that fail to meet international norms	Based on norms related to specific S & E aspects (set by UN, ILO, OECD or other organisations)
positive/ best-in-class	to choose companies based on investor's preferences, values or ethics	a. Investing in sectors with relatively better ESG performance b. Investing in companies because of S & E benefits of their products/services c. Investing in best-in-class or best practice leaders against peers

		based on ESG
Integration	Including ESG factors in investment analysis and decisions	
fundamental	incorporating ESG factors in fundamental analysis, forecasting & valuation	1. Identifying material ESG issues at economy, industry & company level. 2. Assessing the impact of material issues on company's forecasted revenues, profit margins, investments, asset values. 3. Incorporating the changes in forecasted cashflows and cost of capital due to material ESG issues in valuation. 4. Building scenarios to consider ESG uncertainties.
quantitative	integrating ESG factors in systematic rule based strategies for security selection and position weights	1. Establishing a statistical relationship between ESG factors and returns. 2. Setting the parameters of the strategy. 3. Back-testing and evaluating the model 4. Constructing the portfolio
passive indexing	tracking an ESG index systematically	1. Selecting an ESG index 2. Constructing a portfolio replicating the index

Source: Adapted by author from "An Introduction to Responsible Investment" (www.unpri.org) and "ESG integration in listed equity: A technical guide" (PRI,2023) by Principles of Responsible Investment

2.3 ESG Factor Investing

ESG is a latecomer to factor investing and is still evolving regarding its information infrastructure and research-backing as a return factor. Not surprisingly, ESG factor investing is primarily implemented through ESG integration in established quantitative strategies rather than as a standalone strategy.

The following are the critical steps in ESG integration in quantitative strategies.

1. Establishing a statistical relationship between ESG factors and returns.

The first step involves testing an investment hypothesis, usually by statistical analysis of the relationship between proxy variables of ESG and investment returns. One must also assess the correlation between ESG and other factors if the strategy involves multiple factors.

2. Setting the parameters

Parameters to set include the investment universe, the investment objectives, the choice of factors and weighting process, the implementation method and frequency of rebalancing. In setting the parameters the following ESG-based considerations could be used.

a. Applying client-mandated ESG preferences (using exclusion/best-in-class selection) when determining the investment universe.
b. Adding ESG constraints and outcomes to the investment objectives
c. Deciding the measures, indicators and data to be used for the ESG factor
d. Setting any limits on portfolio exposure to ESG metrics
e. Considering frequency of changes in ESG metrics when deciding portfolio rebalancing frequency.

ESG factors could include stock ESG ratings (proprietary or from a third party), individual E, S, or G scores, or ESG momentum (rate of change in ESG score over the past year). One could also use carbon emissions or alternative text-analytics-based data to form the factors. A single ESG factor-based strategy is rare, and it is more likely that the ESG factor is used in conjunction with one or more other factors. In the case of multifactor models, the weight of the factors could be equal or based on risk parity. The implementation strategies used could be long-only or long-short.

3. Back-testing and evaluating the model
In addition to the standard metrics checked in back-testing (such as Sharpe ratio or drawdown), ESG metrics can also be reviewed (aggregate ESG score, GHG emissions intensity). Back-testing could be done over long periods to test the strategy performance over varying market conditions and changes in ESG reporting or regulations.

4. Constructing the portfolio
If back-testing results are encouraging, fund managers may implement the strategy. The security selection and weighting, being rule-based, are automated.

2.4 Key Challenges for ESG Factor Investing
Evolving theories, lack of empirical support and information constraints are critical problems in ESG factor investing. Quantitative strategies are based on validated statistical relationships between stock characteristics and returns or risks. They rely on large amounts of historical data for statistical rigour. In the context of ESG, quant funds can source ESG data and scores from ESG data aggregators and ESG rating providers, respectively. However, the historical data coverage needs to be more extensive across companies and indicators. The inadequacy in historical data weakens the rigour when back-testing the strategy hypotheses, particularly compared to the standards set by academic research for other return factors.

Since returns to factors may be competed away once they become well-established, quant funds need to innovate to refine the strategy and data inputs continuously. Alternative ESG data sets beyond that provided by data aggregators include satellite images, logistics data, social media data, web scraped data and natural language processing-based analysis of textual, audio and video data. While helpful in complementing standard ESG data, the history of such alternative datasets is even shorter, increasing the chances of discovering false patterns.

Regulation can be a challenge as well as an enabler. ESG integration in quantitative strategies is particularly vulnerable to the allegation of greenwashing. Unlike screening, integration does not automatically ensure improvement in the ESG profile of the portfolio compared to the underlying index. On the other hand, it is also possible that the net effect of the ESG factor is so marginal that the portfolio, including the ESG factor, mirrors the portfolio without the ESG factor too closely, again increasing the risk of greenwashing. While minimising tracking error from the base (non-ESG) factor index may be one of the constraints used in portfolio construction, funds will do well to label the ESG integration-based schemes appropriately to avoid regulatory action. It may also be prudent to mention the risk of not being able to achieve ESG objectives in fund documents, both because it is plausible and since investors and the regulator may use different ESG yardsticks than the fund.

Quantitative strategies may result in holdings where it may be challenging to establish a direct link with an intent to consider ESG. If there are regulatory definitions based on the proportion of ESG-compliant holdings, funds can inadvertently violate them in an automated strategy. Funds can partly address the problem by adding rules, such as an initial negative ESG screening or placing constraints on the final weighted average ESG score. When formulated correctly and enforced consistently, regulations can facilitate discipline in the industry, preventing abuse of the ESG label.

2.5 Used cases

This section discusses two used cases of application of ESG integration in quantitative strategies, one from Invesco and one from BlackRock.

Case 1. Invesco Quantitative Strategies

Invesco Quantitative Strategies (IQS) created a carbon-optimised portfolio solution for a client in 2019 to reduce the overall carbon emissions of an existing multifactor strategy in the context of the UK equity universe (Invesco, 2020).

The investment objectives and constraints included the following.

- Minimise the impact on expected performance.
- Maintain the targeted exposures to quality, momentum, and value factors.
- Steady carbon emission reductions over time.

IQS developed an ESG integration-based solution, compared to a negative screening of high carbon intensity sectors, since the latter could have affected the tracking error and industry weight limits. In comparison, ESG integration would be better suited to ensure greater alignment of the portfolio's risk and return characteristics with the benchmark.

The carbon emission reduction criterion included both Scope 1 and Scope 2 emissions. The estimation was based on carbon intensity data since carbon tons per million USD of revenue could be used to make emissions comparable across companies of different sizes, as well as to link ESG criterion with a financial metric.

IQS proposed a two stage-portfolio optimisation as follows.
Stage 1. Construct a minimal tracking-error low-carbon index. This step is done by excluding the worst performers in terms of carbon intensity (to bring carbon emissions below the targeted levels) and reweighting the remaining stocks to minimise the tracking error. The implementation aligns with the method proposed by Andersson et al. (2016).

Stage 2. Apply the multifactor investment process to the low-carbon portfolio created in Step 1 to maintain the targeted exposures to quality, momentum, and value factors.

There were two advantages to adopting the two-stage process. It provided a transparent performance attribution between decarbonising (stage 1) and multifactor management (stage 2). Further, having placed the low carbon constraint in Stage 1, there was no need to trade off carbon characteristics with the base factors in Stage 2.

To back-test the strategy, IQS compared the simulated returns of the new 'UK carbon managed multifactor strategy' against the original 'UK multifactor strategy' over the January 2014 to June 2019 period. The two strategies displayed similar factor exposures (by design) and nearly identical returns (as outcome) while reducing carbon emissions below the targeted levels. These outcomes remained consistent when the strategy was launched in early 2020.

Case 2. BlackRock Sustainable Advantage Large Cap Core Fund – Investor A (BIRAX)

BIRAX is an active sustainability-focused fund from BlackRock. According to BIRAX's prospectus, the fund's investment objective is to provide its investors with total return while maintaining ESG characteristics, climate risk exposures and opportunities relative to the benchmark (Russell 1000). Specifically, it targets superior ESG assessment and lower carbon emissions than the benchmark while including issuers better positioned to capture climate opportunities.

To determine the investable universe, the fund applies exclusionary screens filtering out issuers who derive any revenue from controversial weapons, civilian firearms, tobacco-related products, and those who derive more than 5% of revenues from thermal coal generation, thermal coal mining and oil sands extraction. The fund relies on third-party rating agencies to identify such issuers.

The fund then implements systematic, quantitative models. It further integrates its investment insights with the model-based optimisation process. Specific investment insights may relate to ESG characteristics resulting in superior growth or risk mitigation, themes related to social and environmental considerations. Such ESG characteristics may be related to management quality, governance, controversies, public health, and innovation-oriented research and development.

Note that the fund incorporates ESG once in determining the investment universe and again integrates ESG characteristics with its quantitative models. However, the prospectus does not explain the exact integration method. This implementation is different from that of the IQS case described above.

The fund's performance has closely followed its benchmark over the past five years. As per Morningstar (https://www.morningstar.com/funds/xnas/birax/sustainability), the fund holds ESG concerns central to its investment process. It has several appealing attributes for an ESG-sensitive investor, for instance, low carbon score, low fossil-fuel exposure, and higher involvement in carbon solutions compared to peers. However, the fund has not achieved its goal of avoiding exposure to companies associated with controversial weapons and small arms. It also exhibits relatively high exposure to companies with relatively high controversies.

3. Is ESG a Factor?

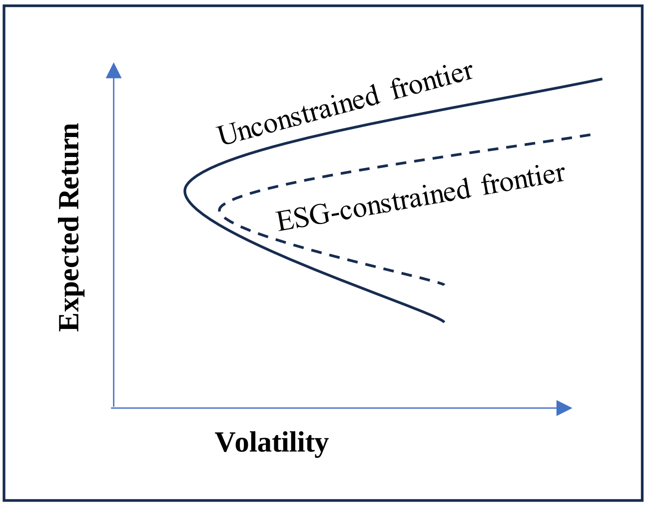
3.1 Under Rational Explanations

The idea that adding ESG constraints to investing will increase returns is counter-intuitive, particularly under risk-based explanations and investor rationality assumptions. To see this, consider an investment opportunity set consisting of N securities. A finite number of securities can, of course, result in an infinite number of portfolios formed by varying security weights in the portfolio, each offering a different risk-return trade-off.

Under the modern portfolio theory, the efficient frontier consists of all the portfolios that are mean-variance optimal; that is, they offer the highest returns for a given level of risk, which also means that they have, for a given level of returns, the lowest level of risk compared to the non-optimal portfolios.

Now consider screening out X securities from N that belong to a negative list of sectors such as tobacco, fossil fuels, or weapons. The screening reduces the opportunity set of investment portfolios. The complete removal of specific sectors makes the constrained portfolios less diversified, increasing systematic risk. An alternative is to use best-in-class screening, which ensures sectoral diversification but retention of only the securities with high scores within each sector. The opportunity set under best-in-class screening differs from negative screening, but it is still smaller than the unconstrained opportunity set. Hence, the ESG-constrained efficient frontier is likely inferior to the unconstrained frontier, as illustrated in Figure 4. Since reduced diversification increases risks, the ESG-screened portfolio must earn higher returns to achieve the same efficiency level.

Figure 4. Unconstrained and ESG-constrained Frontiers



Source: Constructed by Author

Further, let us consider the argument that ESG is a risk factor, constructed as returns on high-ESG-score firms minus returns on low-ESG-score firms. In ESG integration strategies, it may be possible to include all stocks, avoiding the reduction in diversification implicit in screening strategies. However, in practice, ESG integration strategies are also constructed starting from an ESG-screened universe.

Is the risk associated with the ESG factor systematic or idiosyncratic? If it is the former, higher systematic risk should result in greater return and vice-versa under efficient market assumptions. One could choose a portfolio with greater exposure to ESG risks (for instance, more sin stocks) to target higher returns, or one could reduce the exposure to ESG risks (not invest in sin stocks) and accept lower returns. An ESG-sensitive investment approach under the ESG-as-systematic-risk assumption would change the risk-return trade-off but not increase the portfolio efficiency.

ESG risks could be tail risks, in which the conventional mean-variance framework will not effectively capture their implications. Nevertheless, market efficiency (if assumed) will imply that high ESG-risk firms will appear to have better Sharpe ratios. Still, the trade-off will be that they will perform exceptionally poorly under some conditions. If the tail risks are systematic, poor performance will occur under weak economic conditions, offsetting the apparent attractiveness of the portfolio with superior Sharpe ratios measured using portfolio standard deviation as a risk proxy.

ESG risks could also be firm-specific, resulting in implications for cashflows and firm valuation but not for security returns under efficient market assumptions. An impact of ESG on firm performance and cashflows will not impact security returns if markets are efficient.

Finally, consider that ESG can also affect the utility of an investment for an individual investor. Whereas investment utility is usually a function of an investment's expected return and risk, its ESG attribute could be a third parameter. The expected sign of the utility relationship should be positive with return, negative with risk, and positive with the ESG attribute of the investment. Just as an investor's utility is related to investment risk through their risk aversion coefficient, the utility should be related to the investment's ESG attribute through their ESG preference. Investors with greater ESG preference should be ready to accept lower risk-adjusted returns. In aggregate, the ESG preferences of all investors will impact the return-risk relationship of assets.

In short, while we may model ESG as a risk factor or as another attribute, we can show that it will transform the return-risk trade-off but cannot explain why it will necessarily increase risk-adjusted returns. If investors seek portfolios with better ESG attributes, there is no reason for them to expect better returns at a given level of risk.

3.2 Under Behavioural Explanations

The paradigm changes if we bring in some behavioural explanations. Assume, for example, that most investors and analysts are myopic and care more about the short-term earnings performance of firms. Assume further that most managements yield to pressure from the short-term expectations of investors, investing sub-optimally and reducing long-term cashflows. Consequently, most firms fail to achieve their potential long-term value.

But not all managements may display short-termism. There could be a few where managements, perhaps with the support of long-term investors, manage their businesses to be more sustainable. Since the market consists of primarily myopic investors, it fails to price the value of these firms fully. However, over some time, particularly after downturns and economic crises, such firms reveal positive earnings surprises to the myopic investors and analysts, who upgrade their price expectations, but not entirely (since they continue to remain myopic). Though there may be episodic overreaction resulting in an overvaluation of these firms, the long-term trend remains that of undervaluation of ESG, resulting in higher returns over more extended periods.

Short-termism may not be the only behavioural explanation, and there could be others, for instance, those related to varying investors' ESG preferences. These lay the grounds for exploring ESG as a factor which may cause firms with superior ESG attributes to provide higher risk-adjusted returns.

The ESG factor shares its apparent counter-intuitiveness based on risk-based explanations with two other well-known investment factors – quality and low volatility. Other than for size and illiquidity, risk-based explanations appear to be less than intuitive for most well-established factors.

We can now turn our attention towards asset pricing models and empirical research to provide some insights and either validate or raise further doubts on the existence of an ESG factor and the nature of its impact.

3.3 Asset Pricing Models with ESG Factors

Pastor et al. (2021) propose a two-factor asset pricing model, including a market factor and an ESG factor. ESG investors should earn lower returns than non-ESG investors. However, a positive shock, for instance, due to increased demand for sustainable goods, increases the value of high ESG assets and decreases the value of low ESG assets.

Pedersen et al. (2021) propose an ESG-adjusted capital asset pricing model. Equilibrium security prices and returns depend upon the relative dominance of three types of investors – ESG-unaware (U), ESG-aware (A) and ESG-motivated (M). If type-U investors dominate, prices do not capture the superior profitability of high-ESG assets. Hence, expected returns rise with ESG score. If type-A investors dominate, they will bid up the prices of high ESG assets, flattening the relationship between expected returns and ESG scores. If type-M investors are ready to sacrifice returns for ESG, expected returns may decline with the ESG score.

Empirical evidence

Table 2 shows the performance of three well-established ESG indices relative to the underlying (non-ESG) benchmark over ten years ending in October 2023. The table suggests that the ESG indices recorded marginally superior Sharpe ratios compared to their counterparts. However, note that for two indices (MSCI World SRI and S&P 500 ESG), the risk was higher, and the improvement in the Sharpe ratio was mainly due to superior returns in all three cases. Suppose the relative superiority of returns is transitory (due to increasing ESG awareness) and not permanent. In that case, we cannot be sure of superior efficiency since reduced portfolio diversification may offset reduced ESG risks at individual stock levels.

Table 2. Ten Year Performance of Three ESG Indices Relative to Benchmarks

Index	**Annual Return (%)**	**Standard Deviation (%)**	**Sharpe Ratio**
MSCI World SRI	8.93	14.74	0.57
MSCI World	*8.11*	*14.68*	*0.52*
S&P 500 ESG	11.94	15.06	0.79
S&P 500	*11.18*	*14.95*	*0.75*
MSCI KLD 400 Social	11.11	15.30	0.69
MSCI USA IMI	*10.63*	*15.40*	*0.65*

Note: Period ended October 2023

Source: Compiled by author from the websites of MSCI and S&P Global

We have mixed evidence regarding the return predictability of ESG based on empirical research literature. Hong and Kacperczyk (2009) show that sin stocks generate positive abnormal returns. Bolton and Kacperczyk (2020) show that companies with high carbon emissions earn higher stock returns worldwide. Pastor et al. (2022) find that green stocks make lower ex-ante and ex-post returns than brown firms.

However, positive abnormal returns are earned by stocks associated with good governance (Gompers et al., 2003) and higher employee satisfaction (Edmans, 2011). Pedersen et al. (2021) show that different measures of ESG have different signs of impact on returns. Alessandrini and Jondeau (2020) show that applying ESG screening to the MSCI World portfolio can improve the ESG profile without reducing the risk-adjusted returns.

Overall, the empirical evidence does not provide confidence that better ESG attributes result in superior investment outcomes. The results with specific measures hold more promise than using overall ESG ratings as a proxy.

The lack of comparability of ESG data across companies due to a lack of standards has been an underlying issue (Amel-Zadeh & Serafeim, 2018). There is hope on this front, with increasing development, regulatory enforcement and convergence of ESG disclosure standards. However, ESG ratings remain unregulated, fragmented, and, as a consequence, highly divergent across rating providers (Berg et al., 2020). Avramov et al. (2022) build a model and empirically demonstrate that ESG uncertainty, as reflected in ESG ratings, explains the mixed evidence on the relationship between ESG score and alpha of portfolios.

4. Implications

It is evident from the preceding sections that the practice of ESG investing has grown marvellously from its old antecedents, starting with personal values-based investing. Over time, the industry has split into impact investing in the private equity space and ESG investing in the public equity space. There have been two critical shifts with the rise in ESG investing. One, institutional investors in public equities predominantly adopt the ESG opportunities and risks perspective, focussing on ESG inputs rather than outcomes. Two, reliance on third-party ESG data, ratings and indices has enabled the industry to scale up cost-effectively. The increasing concern regarding environmental issues, the rising ESG awareness and sensitivity among investors and the growing share of passive investing are broad trends enabling the rapid growth of ESG investing.

ESG investing strategies have evolved. ESG integration has overtaken screening as the dominant investment strategy. Factor investing occurs in the ESG space primarily through quantitative ESG integration strategies. A standard template is to start with an ESG-filtered investment universe and then build a multifactor strategy, where ESG characteristics are either integrated directly as an ESG factor or indirectly as constraints in portfolio construction. An alternative is to embed ESG data into definitions of existing factors, such as quality. Quality and low-volatility portfolios tend to have better ESG profiles than the market (Ang, 2020).

Innovation and differentiation are driven by research, back-testing the relation of returns with different components, indicators and alternative data sources. Positioning and marketing are conditional upon target investor demand and regulatory guidelines. Aggressive claims may give rise to allegations of greenwashing, provoking backlash from regulators and policymakers. The evolving best practices to prevent loss of reputation and regulatory action include appropriate labelling, explaining the ESG investment objectives and broad strategy, and highlighting the risk factors of such strategies in fund documents and investor communication.

Theoretical foundations for ESG as a factor are still evolving, integrating ESG preferences, awareness and motivation in existing asset pricing models. Rationally, the ESG factor is counter-intuitive, similar to low volatility and quality factors, making behavioural explanations necessary. We have mixed evidence of superior portfolio performance. Limitations of information infrastructure, particularly ESG ratings, result in measurement errors, causing challenges to empirical research.

Empirical evidence does not support the hypothesis that better ESG performance will result in superior return performance. However, there is some promise regarding focussing on more specific aspects of ESG.

The discipline of quantitative investing requires academic research to debate, develop different measures and then validate the factors using data from several decades and across countries. Innovations in implementation are incremental. In ESG factor investing, the practice has run ahead of evidence, making it seem like a fad. More robust information infrastructure and precise insights from academic research will make the growth healthy and sustainable.

5. Conclusion

This chapter charts the growth of ESG investing and explains the practice of ESG investing in general and ESG factor investing in particular. The chapter also discusses the theoretical debate, developments and empirical evidence about ESG as a factor. ESG investing has grown very fast, enabled by market trends and increasing concerns regarding sustainability. However, its informational and research foundations still need some strengthening. The jury is still out on the efficacy of the ESG factor. Caution is warranted, requiring ESG integration to be appropriately calibrated in portfolio construction and carefully explained in investor communication.

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Chapter-7

MULTI-FACTOR INVESTING: MIX, INTEGRATE, OR SEQUENTIAL SCREENING?

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1. Introduction

What is multi-factor investing?

As nutrients are to the food, so are factors to the assets. Each food item can be considered a bundle of nutrients, and a balanced diet comprises the right mix of nutrients. Similarly, each asset class can be considered a bundle of factors such as economic growth, inflation, interest rates, currency, credit, etc.

For example, stocks and bonds are traditionally considered as good diversifiers.

However, a close analysis of factors driving stock and bond performance shows that they similarly react to shock to common underlying factors such as inflation. A sudden spike in inflation and interest rates often negatively impacts stocks and long-term bonds. In contrast, sudden drops in inflation and interest rates, or quantitative easing, favorably impact stocks and long-term bonds. This means stocks and bonds are not good candidates for diversification as they fail to offer protection against inflation risk. Hence, the focus of asset allocation must be on diversifying in a manner that offers protection against a specific factor risk rather than just adding several assets to the investment portfolio. The Global Financial crisis brought this to the fore when several multi-asset portfolios of sizeable sovereign wealth funds, endowment, and pension funds failed to avoid significant drawdowns. The reason was that they had multi-asset portfolios that were not genuinely diversified portfolios to protect against factor risk.

Within an asset class like equity as well, the value of diversification is paramount. How and how much to diversify has remained an important issue. Extreme concentration exposes investors' high idiosyncratic risk as too much diversification may end up in 'diworsficiation,' and one might hold too many stocks. With the integration of global capital markets with the evolution of technology and global fund flows, the benefits of diversification based on geographic area (developed vs. emerging markets) and size buckets (small, mid, and large-cap stocks) have reduced considerably since the beginning of the 21st century. A new and attractive diversification opportunity has emerged with the emergence of factor investing. While such factor diversification works better in long-short portfolios, long-only portfolios can benefit from such an approach. For example, value investing works in harmony with business cycles and works best at the turn of the business cycle from the trough to recovery.

On the other hand, momentum is considered an all-weather investment strategy, but it runs the tail or crash risk and large drawdowns. Low volatility and quality investing deliver returns through its resilience during market turmoil by losing less, proving counter-cyclical. The right combination of smart beta or factor investment strategy can offer superior risk-adjusted returns. The question is how to build a multi-factor investment strategy.

2. Multi-Factor Investing: Mix, Integrate, or Sequential Screening.

There are at least three popular ways to construct multi-factor equity portfolios: Mix, Integrate, and Sequential screening. Academics and practitioners are yet to come to a consensus about the superiority of any approach. Hence, it is vital to understand each of them with their pros and cons.

2.1 Pure and Mix

The first approach allocates funds across two pure-factor portfolios. For example, Wesley Gray, Alpha Architect's founder, claims that such an approach allows pure exposure to both value and momentum investment strategies and benefits from the low correlation between the two investment strategies (Gray, 2014). This is similar to the asset allocation approach proposed by the Modern Portfolio Theory (Markowitz, 1952), which emphasizes that the portfolio comprises assets with negative, moderately positive, and no correlation. Such a portfolio helps reduce diversifiable risk and enhance the reward-to-risk ratio.

A mixed approach to multi-factor investing must allocate funds across pure-factor portfolios. Allocation to factors with low correlation will help improve risk-adjusted returns without compromising the purity of individual factor portfolios. For example, if one allocates 50% to momentum and 50% to value portfolios, the low correlation between value and momentum portfolios will improve the risk-reward trade-off. Such a pure and mixed approach has the benefit of retaining the purity of momentum and value investment strategies while benefiting from the portfolio effect.

However, it has an implicit drawback. For example, if momentum and value have a low correlation, many strong positive momentum stocks may invariably score poorly on value and vice versa. One might have exposure to stocks with unfavorable exposure to at least one factor.

The multi-factor investing approach suits the index manufacturers, index funds, and ETF providers best as they can offer a combination of pure factor or smart beta indices as multi-factor indices. For example, the National Stock Exchange, India's largest stock exchange, has created multi-factor indices based on pure-factor indices, as shown in Table 1 below.

Table 1: National Stock Exchange of India- Multi-Factor Indices[1]

Index	Factor Weights				Selection	Weights
Nifty Alpha-Low Volatility 30	50%	50%			Top 30 stocks based on the weighted average percentile score	Based on weighted average factor level Z Score. Weights of stocks are capped at 5%
Nifty Quality Low Volatility 30		50%	50%			
Nifty Alpha Quality Low Volatility 30	33.33%	33.33%	33.33%			
Nifty Alpha, Quality, Value, Low-Volatility 30	25%	25%	25%	25%		

Using any other approach to construct multi-factor indices by such index may result in cannibalization of single-factor indices and overcrowding of indices. Instead, offering readymade multi-factor indices with predetermined weights and their performance track record allows investors to create multi-factor portfolios and asset management companies to offer readymade multi-factor solutions by simply offering a combo of single-factor index funds or ETFs.

2.2. Integrated Approach

The integrated approach to multi-factor investing aims to eliminate the inherent issue of mixing pure-factor portfolios with extreme factor

[1] https://www.niftyindices.com/Methodology/Method_NIFTY_Equity_Indices.pdf, accessed on November 25, 2023

characteristics. As discussed earlier, the best-ranked value stock from a given universe may score the worst on momentum ranking and vice versa. Therefore, while the pure mixing approach looks for specialists, the integrated approach looks for all-rounders. In an integrated approach, one looks to construct a multi-factor portfolio by choosing stocks that perform the best on an aggregate basis. The following example in Table 2 helps us understand the difference between the mix and integrated approach.

Table 2: Construction of multi-factor portfolio using an integrated approach

Stocks	Momentum Rank	Value Rank	Average integrated ranks
A	1	10	5.5
B	2	4	3
C	3	3	3
D	4	5	4.5
E	5	7	6
F	6	2	4
G	7	6	6.5
H	8	1	4.5
I	9	9	9
J	10	8	9

If an investor wants to construct a three-portfolio using a momentum investment strategy, she chooses stocks A, B, and C. If she wants to create a value investment strategy, she may choose stocks H, F, and C. Suppose she wants to create an equally weighted multi-factor portfolio. In that case, she must allocate half of her capital to a momentum portfolio and half to a value portfolio. However, she may invest funds in the worst-ranked value stock A while doing so. Therefore, to overcome such a challenge, one might follow an integrated approach and look for stocks with the highest combined rank based on twin criteria of value and momentum. Such an integrated approach selects stocks B, C, and F. Such an approach helps eliminate the stocks with high attractiveness on one factor but extremely unattractive characteristics on the other. However, the critics of such an approach complain that this is a compromise strategy and eventually results in a portfolio of average performers, both here and there. AQR Capital, co-founded by Cliff Asness and others, follows such an approach to multi-factor investing. However, this approach is familiar, and it has been used by some or other investors much before the emergence of an era of smart beta or factor investing.

While Benjamin Graham, the father of value investing, followed a more traditional value investing approach to look for cheap stocks, his most successful disciple and renowned value investor, Warren Buffet, followed an approach different than his guru, pursued by the late Charlie Munger, his long-standing ally at Berkshire Hathway. Remembering a conversation with Charlie Munger way back in the early 1970s, Mr. Buffet told CNBC in 2016, "He weaned me away from the idea of buying very so-so companies at very cheap prices, knowing that there was some small profit in it, and looking for some really wonderful businesses that we could buy in fair prices,"[2] They focused on quality at a reasonable price and on wounded eagles rather than ducks. They searched for quality stocks available at attractive valuations to benefit from depressed market sentiment caused by external shocks or temporary setbacks quality businesses face.

Joseph Piotroski, in his famous 2000 paper, introduced the F-score, aka fundamental score, that helps separate value trap and value stocks from the universe of cheap stocks. The F-score offers an aggregate assessment of the firm's financial health and operating efficiency. Firms with high F-scores are quality firms available at cheap valuations and are true-value stocks, and cheap stocks with low F-scores are junk stocks or value traps (Piotroski, 2000).

In a book on magic formula investing (Greenblatt, 2010), the celebrated hedge fund manager Greenblatt offers a magic formula that ranks securities based on twin criteria of value and quality proxies of EV/EBIT, a measure of value, and ROIC, a measure of quality. The stocks ranked at the top of the list are dubbed

[2]https://www.cnbc.com/2023/11/28/charlie-munger-investing-sage-and-warren-buffetts-confidant-dies.html, accessed on November 28, 2023

'quality at a reasonable price.' The portfolio comprising such stocks might outperform the broader market portfolio.

2.3 Sequential screening

This approach calls for developing a multi-level screening based on different criteria by defining primary and secondary criteria. Such criteria overcome the limitations of mixed and integrated approaches, but they might need higher turnover and high implementation costs. The cases where sequential screening was applied are given below.

A paper titled Conservative Formula: Quantitative Investing Made Easy (Blitz & van Vliet, 2018) offered a simple yet robust way to combine low-volatility investing with momentum and value investing. Conventional low-volatility investing relies on winning by losing less; hence, it can be frustrating for investors to implement and stick to such an investment strategy. In addition, the low-volatility investment strategy may include stocks approaching slow and painful decline and hence qualify as low-volatility stocks. Following the two-stage sequential screening, the core of the strategy remains a low risk to enhance the attractiveness of low volatility investment strategy and add momentum and value boosters. Such an approach helps construct a low-risk, cheap -and strong portfolio. Robeco has followed this approach to manage its multi-billion dollar conservative portfolio over nearly two decades.

- Select the top 1000 stocks (or any other number) based on the size.
- Arrange stocks based on their historical volatility in descending order.
- The universe is divided into equal parts (500 stocks each): Low-volatility and high-volatility.
- Within low-volatility universe stocks, the stocks are ranked based on strong price momentum and high pay-out yield (a proxy for value).
- The stocks within low volatility Universe are then ranked based on average momentum and pay-out yield rank.

- Top 100 stocks based on such combined rank form conservative portfolios with low risk, strong price momentum, and cheap valuation characteristics.
- Conversely, stocks are 100 stocks from a high volatility universe with weak price momentum, and low pay-out yield constitute a speculative portfolio.
- The conservative portfolio powered by low-risk, strong, and cheap characteristics should outperform the speculative and broad markets.

Pim Van Vliet, on his website paradoxinvesting.com, regularly updates the performance of volatility decile, conservative, and aggressive portfolios. Table 3 shows the performance of Low volatility decile (LV), high volatility decile (HV), conservative and speculative portfolios.

Table 3: Compounded return, volatility, and return/risk of LV, HV, Conservative and Speculative portfolios for top 1000 US stocks[3] (1929-2021)

1929-2021	LV	HV	Conservative	Speculative
Return (comp)	10.50%	6.60%	15.30%	3.00%
Volatility	13.30%	35.90%	16.40%	35.30%
Return/Risk	0.79	0.18	0.93	0.08

Source: paradoxinvesting.com

It is visible that the risk anomaly is strong in the extremely volatility decile portfolios in the long run, with the LV portfolio delivering compounded returns of 10.5% over a 93-year long period in US markets with an annualized volatility of 13.3%. In contrast, the HV portfolio delivered a mere 6.6% compounded annual returns with 35.9% annualized volatility during the same period. The outperformance of the LV portfolio on both the return and risk front resulted in a return-to-risk ratio for the LV portfolio of 0.79, whereas the same is just 0.18 for the HV portfolio. So, while risk anomaly deliver superior risk-adjusted performance, such performance can be enhanced by benefiting

[3] https://www.paradoxinvesting.com/data/

from favorable momentum and value characteristics. The conservative portfolio delivered 15.3%-compounded returns with 16.4% annualized volatility. Moving away from a pure LV strategy increases volatility slightly, but the sharp return jump improves the return-to-risk ratio to 0.93.

On the contrary, the speculative portfolio delivered just 3% compounded returns with 35.3% volatility. While the speculative portfolio's volatility is similar to the HV portfolio, its poor value and momentum characteristics drag its return much lower than even the HV portfolio. Hence, it earned a return-to-risk ratio of just 0.08. Adding momentum and value to a low-volatility investment strategy helps enhance its performance.

Joshipura & Joshipura (2020) report similar results in their study on top 500 stocks by size in Indian stock market constructed portfolios intending to boost returns of low volatility investment strategy. They followed a stage sequential screening process to construct a low-volatility portfolio with a momentum booster.

- Select the top 500 stocks based on size.
- Rank stocks in descending order based on their last twelve months' price momentum
- Divide the stocks into two halves: The strong and weak momentum universe.
- Within a universe of 250 strong momentum stocks, rank stocks based on their historical volatility in ascending order.
- Select the top 50 low-volatility stocks to construct an equal-weighted angel portfolio comprising stocks with low volatility from a strong momentum universe.
- Stocks with high volatility from weak momentum are called evil portfolios.

Table 4: Compounded return, volatility, and return/risk of LV, HV, Angel, and Evil portfolios for top 500 Indian stocks (2004-2018)

2004-2018	LV	HV	Angel	Evil
Excess return (comp)	11.57%	3.02%	16.16%	-3.69%
Volatility	18.47%	41.89%	18.06%	46.13%
Sharpe ratio	0.72	0.072	0.89	-

Source: Joshipura and Joshipura (2020)[4]

Table 4 shows that there is a substantial risk anomaly in Indian stock markets in the first and second decade of the 21st century, with LV quintile portfolio delivering 11.57% compounded excess returns with 18.47% annualized volatility with Sharpe ratio of 0.72 compared to corresponding numbers of 3.02%, 41.89% and 0.072 for HV quintile portfolio. Further, the Angel portfolio boosts return significantly to 16.16% without any increase in volatility, which lifts the Sharpe ratio of the angel portfolio to 0.89 compared to the Sharpe ratio of 0.72 for the pure LV portfolio. On the other hand, evil portfolios further worsen the poor performance of HV portfolios. The high volatility and weak momentum turned out to be a deadly combination that pushed the compounded return of the evil portfolio to negative, with annualized volatility shooting up to 46.13%, even higher than the HV portfolio's volatility.

In summary, there is merit in following multi-factor investment strategies as they can benefit from exposure to more than one factor. However, such strategies come with implementation costs and challenges, and no one standard dominant approach exists. All available approaches to constructing multi-factor portfolios have pros and cons, and one has to choose the best approach according to one's needs and convenience.

[4] http://dx.doi.org/10.21511/imfi.17(2).2020.11

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Chapter-8

MACHINE LEARNING FOR SMART BETA INVESTING

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Abstract

The chapter delves into the intersection of machine learning and smart beta investing. Smart beta investing, a blend of passive and active strategies, aims to outperform traditional market-cap-weighted indices by focusing on factors that historically yield higher returns or lower risk. Traditional smart beta approaches employ rule-based strategies based on historical financial metrics and market data. However, the integration of machine learning has transformed smart beta investing, introducing adaptability, real-time insights, non-linear patterns, and the utilization of alternative data sources. This chapter discusses the challenges faced by traditional methods, the evolution towards machine learning-based approaches, global practices, and applications of machine learning in smart beta investing and presents a numerical illustration of portfolio optimization. Machine learning applications have enhanced factor selection, risk management, predictive analytics, portfolio allocation, andbacktesting and also highlight the future of machine learning in smart beta investing. These advancements enable investors to navigate the dynamic financial landscape, optimize their strategies, and make more informed investment decisions, potentially outperforming traditional benchmarks. The chapter highlights that the future of smart beta investing is

increasingly intertwined with machine learning, offering investors powerful tools to succeed in modern financial markets.

Keywords: Smart beta investing; Machine learning; Applications; Numerical Evidences; Portfolio Optimisation

Introduction

Smart beta investing, also known as factor-based or strategic beta investing, is an investment approach that combines elements of both passive and active investing. It focuses on factors or attributes that have historically generated higher returns or reduced risk than traditional market-cap-weighted indices(Arnott et al., 2016). Smart beta investing, predating the advent of machine learning, relied on a spectrum of traditional quantitative finance strategies and factors. One approach involved equal weighting, which placed the same importance on all assets, mitigating the dominance of larger corporations and fostering diversification(Shepherd, 2014; White & Haghani, 2020). Minimum variance strategies sought to create portfolios with minimal price volatility by concentrating on assets with historically low price fluctuations (Cazalet et al., 2013). Risk parity methodologies allocate assets according to their risk contributions, ensuring an equal risk weighting across the portfolio's constituents. Value investing prioritized undervalued assets through indicators like price-to-earnings (P/E) ratios or dividend yields. Momentum strategies selected assets with recent strong performances, while quality investing concentrated on stocks with robust fundamentals, such as profitability and low debt (Blitz, 2016).

Additionally, low-volatility investing focused on constructing portfolios using assets that exhibited lower price volatility, while dividend yield strategies emphasized high-yield assets to cater to income-seeking investors. Market capitalization also played a role in investment strategies, emphasizing specific segments like small-cap or large-cap stocks (Hsu, 2014). Fundamental indexing departed from traditional market-capitalization-weighted indices, instead using financial metrics to determine asset weights. Factor-based investing, a prominent smart beta strategy (Carson et al., 2017), leverages factors like value, momentum, size, quality, and low volatility to select and weight assets, with the systematic use of these factors helping achieve specific investment objectives (Amenc & Goltz, 2013).

These conventional smart beta strategies were typically rule-based and relied on historical financial metrics and market data. However, incorporating machine learning and data-driven methods has revolutionized smart beta investing, bringing adaptability, non-linear patterns, alternative data sources, and dynamic responses to changing market conditions into the fold. Machine learning algorithms enable more sophisticated factor selection, optimization, and portfolio construction, enhancing efficiency and potential returns(Emi, 2011; Roy et al., 2015). By harnessing advanced data-driven techniques, smart beta investing has evolved into a more dynamic and responsive approach, proving invaluable in modern investment landscapes. The study will review the global practices of smart beta investing and challenges in the traditional method of smart beta investing in section 2. The evolution from traditional methods to Machine learning methods, why it happened, and what specific global practices are followed are discussed in Section 3, followed by applications of smart beta investing and its numerical applications, especially for portfolio analytics, which are highlighted in Sections 4 & 5. The future aspects of smart beta investing are given in section 6. Finally, the study will conclude in Section 7.

1. **Global Practices of Smart Beta Investing**

Smart beta investing has witnessed a global evolution, transcending traditional market-cap-weighted indices, as investors seek innovative strategies to enhance returns and manage risk. In the United States, quantitative asset managers are at the forefront of smart beta adoption, leveraging machine learning and data-driven approaches to construct dynamic portfolios(Sunrise & Elizabeth, 2019). These strategies tap into diverse data sources, including financial reports and social media sentiment, enabling real-time adaptation to market conditions. Meanwhile, Europe strongly emphasizes risk management within smart beta strategies, utilizing machine learning algorithms to predict market volatility and identify tail risk events. This approach aims to secure higher risk-adjusted returns and mitigate downside market movements(Farrugia et al., 2021). In Asia, countries like Japan and South Korea focus on portfolio optimization, using machine learning to consider transaction costs, liquidity, and sector exposure limits(Ali et al., 2018). Predictive analytics also play a pivotal role in emerging markets, such as Brazil and India, empowering investors to make proactive decisions based on forecasts. Across the globe, particularly in Canada and Australia, comprehensive backtesting helps investors refine and validate their models(Lodhia & Mitchell, 2022; Weber, 2012). The utilization of alternative data sources, factor diversification, ESG integration, and portfolio customization are additional trends shaping innovative beta practices globally(Jung & Song, 2023). These practices underscore the adaptability and innovation within the smart beta landscape, catering to the complexities of modern financial markets.

2.1 Challenges with Traditional Methods of Smart Beta Investing

While widely used, the historical method of smart beta investing faces several notable challenges. First and foremost, this approach relies heavily on past market data and historical financial metrics to select and weight assets(Ding et al., 2022). Consequently, it may struggle to adapt to dynamic market conditions and unforeseen events, as it does not inherently incorporate real-time information or change investor sentiment(Shad et al., 2019). In rapidly evolving markets, historical methods can lag behind and fail to capture emerging trends or sudden market shifts, potentially resulting in suboptimal portfolio performance. Another challenge lies in the potential for overfitting historical data. Selecting and weighting assets based on historical patterns can lead to portfolios that are too tailored to past conditions. This can result in poor out-of-sample performance when market dynamics change, making it difficult to predict whether historical outperformance will persist(Kim, 2018).

Furthermore, these approaches assume that historical relationships between factors and asset performance will continue. While this assumption can be valid over specific periods, it may not hold indefinitely, especially during market turmoil or structural shifts(Heggedal et al., 2011). The inability of historical methods to adapt to these paradigm shifts can expose investors to significant risk and potential losses. Additionally, the reliance on easily accessible financial metrics and traditional data sources can lead to crowded trades, where many investors are pursuing the same smart beta strategies based on the same data(White & Haghani, 2020). This overcrowding can result in diminishing returns as assets become overpriced, and it becomes challenging to find undervalued opportunities. Finally, there is a risk of model instability. Historical data can be noisy and subject to occasional irregularities, leading to unstable factor models(Hsu et al., 2015). The instability of these models can result in frequent changes to portfolio compositions, transaction costs, and tax inefficiencies, ultimately eroding returns. In light of these challenges, modern smart beta strategies increasingly incorporate machine learning and alternative data sources to overcome some of the limitations of historical approaches (Gopalkrishnan, 2013). These advancements offer adaptability, real-time insights, and the potential to navigate changing market dynamics more effectively.

2. Evolution from Traditional Approach to Machine Learning Based Approach

The evolution of smart beta investing from traditional approaches to machine learning has been driven by the desire to improve these strategies' adaptability, efficiency, and predictive power. Traditional smart beta methods primarily rely on historical data and predefined financial metrics, making them less responsive to dynamic market conditions. Machine learning, on the other hand, leverages advanced algorithms and alternative data sources to enhance portfolio construction and optimize risk-adjusted returns(Silvasti et al., 2021). For example, machine learning can process structured and unstructured data, such as social media sentiment, satellite imagery, and economic indicators, to capture real-time market sentiment and emerging trends. These non-traditional data sources can provide valuable insights for asset selection and portfolio weighting. By incorporating such data, machine learning models can adapt to market shifts more effectively than traditional smart beta strategies.

Furthermore, machine learning allows for identifying complex and non-linear relationships between factors and asset performance. Traditional approaches often assume linear relationships between variables, limiting their effectiveness. Machine learning models, such as neural networks and random forests, can capture intricate, non-linear patterns in the data, leading to more accurate predictions(Baesens et al., 2021). One practical example is using natural language processing (NLP) algorithms to analyze financial news and social media content. Sentiment analysis tools can gauge the collective market sentiment toward specific assets or sectors in real-time. Machine learning models can then use this sentiment data to make informed investment decisions, adapting to changing market sentiment. Machine learning also offers robust risk management capabilities(Parn & Edwards, 2019). Advanced models can assess and predict market volatility, helping investors make more informed decisions during turbulent times. Additionally, machine learning can provide portfolio optimization by considering constraints, transaction costs, and liquidity(Zey, 2001). The transition from traditional smart beta to machine learning-based approaches represents a significant step forward in harnessing the power of data and algorithms for investment management. By embracing machine learning, investors can potentially improve the adaptability and performance of their smart beta strategies in today's ever-changing and data-rich financial markets.

3.1 Global Practices of Machine learning and Smart Beta Investing

Machine learning-based approaches have transformed smart beta investing, and several countries have embraced these applications to enhance their investment strategies. For instance, in the United States, quantitative asset managers employ machine learning models to develop dynamic smart beta portfolios. These models analyse vast data, including financial reports, market news, and social media sentiment, to select the most relevant factors driving asset performance(Hain et al., 2022). By dynamically adjusting portfolio weights in response to real-time data, these strategies can capture market opportunities and adapt to changing conditions, such as shifts in market sentiment during volatile periods.

Countries like the United Kingdom and Germany have adopted machine learning for smart beta investing to optimize risk management in Europe. Machine learning algorithms can predict market volatility and identify potential tail risk events, helping investors construct portfolios that balance risk and return more effectively(Thomas, n.d.). By incorporating these advanced risk metrics into their strategies, investors aim to achieve higher risk-adjusted returns and better protection against downside market movements. Asian countries, including Japan and South Korea, have integrated machine learning into their smart beta strategies for enhanced portfolio optimization(Blitz, 2016). These countries leverage machine learning algorithms to optimize portfolios while considering constraints such as transaction costs, liquidity, and sector exposure limits. This approach ensures the portfolio aligns with the investor's objectives while minimizing trading costs and sector concentration risks(Sunrise & Elizabeth, 2019).

In emerging markets like Brazil and India, machine learning is playing a crucial role in enabling predictive analytics in smart beta investing (Jayant Sathaye (USA), Oswaldo Lucon (Brazil), 2012). Investors can make proactive investment decisions and capitalize on emerging market trends by forecasting future asset prices and returns. The ability to harness these predictive insights has been instrumental in navigating evolving market conditions and achieving more favourable investment outcomes. Across the globe, machine learning has expanded the back-testing capabilities of savvy beta investors. Using historical data and machine learning models, countries like Canada and Australia can conduct robust back testing to comprehensively evaluate smart beta strategies' performance (Ellis et al., 2014). This rigorous performance analysis helps investors refine their strategies, allowing for a deeper understanding of potential risks and rewards.

In summary, machine learning-based applications have ushered in a new era of smart beta investing, enhancing these strategies' adaptability, predictive power, and real-time data integration. Countries worldwide leverage these technologies to stay competitive in today's dynamic and data-rich financial markets. Using machine learning, they are improving portfolio management, risk mitigation, and investment decision-making, ultimately seeking superior financial outcomes.

3. Application of Machine Learning in Smart Beta Investing

Machine learning has found many applications in smart beta investing, revolutionizing how investors construct and manage portfolios. These applications have become advantageous due to their ability to harness vast amounts of data, discover non-linear relationships, and adapt to changing market conditions. Here, we explore some key applications and their advantages in the context of smart beta investing.

1. Factor Selection and Combination: Machine learning models excel at identifying relevant factors affecting asset prices. For example, they can uncover intricate relationships between macroeconomic indicators, financial ratios, and asset returns. By employing algorithms like Random Forest or Gradient Boosting, investors can select factors that offer the best risk-adjusted returns, helping them create smart beta portfolios that outperform traditional market-cap-weighted benchmarks. The advantage lies in uncovering non-obvious factors that drive returns and reducing reliance on simplistic models.

2. Risk Management and Optimization: Machine learning enhances risk management by predicting portfolio risk and tail events. These models can provide early warnings of market downturns, enabling investors to take proactive measures to protect their portfolios. Additionally, machine learning-driven optimization techniques help construct portfolios that maximize returns while staying within predefined risk constraints. Investors achieve more stable and reliable returns by minimizing portfolio volatility and tail risk.

3. Predictive Analytics: Machine learning enables predictive analytics by forecasting asset prices, volatility, and other financial metrics. For instance, recurrent neural networks (RNNs) can predict future stock prices based on historical data and current market conditions. This predictive power helps investors make informed investment decisions and capture potential market opportunities. The advantage lies in acting on forecasts and trends rather than reacting to historical data.

4. Portfolio Allocation and Rebalancing: Machine learning algorithms optimize portfolio allocation and rebalancing by considering transaction costs, liquidity, and other constraints. For example, reinforcement learning models can adapt portfolios in real-time to changing market conditions and emerging trends. This dynamic allocation ensures the portfolio remains aligned with the investor's objectives while minimizing trading costs. The advantage is the ability to maximize efficiency and reduce unnecessary turnover.

5. Backtesting and Model Validation: Machine learning facilitates robust backtesting of smart beta strategies, allowing investors to evaluate historical performance rigorously(Adewumi & Akinyelu, 2017). By leveraging historical data and complex models, investors can gain deeper insights into how their strategies would have performed in various market conditions. This process helps refine and validate models, ensuring they can withstand real-world scenarios. The advantage is increased confidence in the strategy's effectiveness.

In summary, machine learning applications in smart beta investing have become advantageous due to their ability to discover complex relationships, enhance risk management, offer predictive insights, optimize portfolio allocation, and support thorough backtesting (Saravanan et al., 2012). These technologies enable investors to stay competitive, adapt to evolving market conditions, and potentially outperform traditional benchmarks, ultimately leading to more efficient and informed investment decisions. The future of smart beta investing is increasingly intertwined with machine learning, providing investors with sophisticated tools to navigate the complexities of modern financial markets.

4. Numerical Evidence of Smart beta investing for Portfolio Optimization Using Machine Learning

5.1 Portfolio Optimization Problem

You have an initial investment portfolio with equal weights in five stocks: TVS, Tata Steel, SBI, Infosys, and ICICI. You want to optimize the portfolio allocation for a one-month investment period. The objective is to maximize the portfolio's expected return while maintaining a specific risk level. The historical returns data for the five stocks over the given period is provided. (refer to Table 1)

Table 1: Returns of stocks

Date	*TVS Return*	*Tata Steel Return*	*SBI Return*	*Infosys Return*	*ICICI Return*
31-05-2023	0.2224	0.1063	0.0551	0.1022	0.0001
01-06-2023	-0.0982	0.0462	-0.0965	0.0339	0.0368
02-06-2023	0.2360	-0.0755	0.0088	0.0664	0.0565
03-06-2023	0.2007	-0.1114	-0.0061	0.0406	-0.0825
04-06-2023	0.1283	0.0652	0.1000	0.0779	0.1264
05-06-2023	-0.1228	-0.0346	0.1732	0.0734	0.0756
06-06-2023	0.1581	-0.1699	-0.0302	-0.1000	0.0063
07-06-2023	0.1381	-0.0227	-0.0093	0.0824	0.0213
08-06-2023	-0.0888	-0.1075	-0.0297	0.0562	-0.0732
09-06-2023	-0.0665	-0.1017	-0.1160	-0.0211	-0.0607
10-06-2023	-0.1130	0.1290	0.0101	-0.1329	0.0484
11-06-2023	0.0106	-0.0925	0.0307	0.0408	-0.0429
12-06-2023	0.0247	-0.0755	-0.0570	-0.0273	-0.0296
13-06-2023	-0.0253	-0.2100	0.0274	0.0900	-0.0183
14-06-2023	-0.0622	-0.0911	-0.0878	0.0160	0.0271
15-06-2023	0.0282	-0.0585	-0.0421	0.0599	-0.1391
16-06-2023	0.1433	0.1484	-0.0004	-0.0231	0.0243
17-06-2023	0.1452	-0.0740	0.0478	-0.0428	-0.0125
18-06-2023	-0.0577	0.1262	-0.1024	0.0160	-0.0456
19-06-2023	0.0084	-0.0397	-0.2213	0.0524	-0.1271
20-06-2023	-0.0861	-0.0024	-0.1251	-0.0719	-0.1914
21-06-2023	0.1855	0.2495	0.2018	0.1168	0.2193
22-06-2023	-0.0093	0.0937	-0.0274	-0.0084	0.0013

23-06-2023	-0.1164	-0.0489	0.0810	0.0330	0.0320
24-06-2023	0.0837	-0.0378	0.0654	-0.0644	-0.0169
25-06-2023	-0.0591	0.0979	0.0473	-0.0864	0.0888
26-06-2023	0.1112	0.0415	0.0959	-0.0360	-0.0188
27-06-2023	0.1152	0.0112	-0.0050	0.0002	-0.0229
28-06-2023	0.1017	0.0801	0.0265	-0.0379	0.0935
29-06-2023	-0.0794	0.0234	0.0014	-0.0223	-0.0417
30-06-2023	-0.0370	-0.0591	-0.0321	0.0353	-0.0394
01-07-2023	0.0689	0.1685	0.0398	-0.0846	0.0521
02-07-2023	0.1044	0.0416	0.0334	0.0864	0.0271
03-07-2023	0.0049	-	0.0861	0.0097	0.0018
04-07-2023	0.1409	-0.0718	-0.0125	-0.1065	0.0059
05-07-2023	0.0818	0.1164	-0.0050	0.0613	0.1589
06-07-2023	0.0200	0.0782	-0.0522	-0.0434	-0.0226
07-07-2023	0.0582	0.0384	0.1328	0.0778	0.0420
08-07-2023	0.0364	0.1179	-0.1179	-0.1000	-0.0152
09-07-2023	0.0847	0.0225	-0.0900	-0.0166	-0.0747
10-07-2023	0.0961	0.0756	0.1862	0.0241	0.0815
11-07-2023	-0.0097	-0.0138	0.0465	0.0572	0.0245
12-07-2023	0.0732	0.0536	-0.0332	0.0654	0.0208
13-07-2023	-0.1008	0.0104	0.0108	0.0988	0.1169
14-07-2023	-0.0230	-0.0486	-0.1560	0.0192	-0.1193
15-07-2023	-0.0949	-0.1622	-0.0699	-0.0354	-0.1181
16-07-2023	0.0748	0.0410	-0.0141	0.0581	0.0208
17-07-2023	-0.1278	-0.0330	0.0898	0.0266	0.0056
18-07-2023	-0.0605	-0.0138	-0.0386	0.0594	-0.0371
19-07-2023	-0.0678	-0.0083	0.1237	0.0433	0.0996
20-07-2023	0.0972	0.0644	0.0534	0.0542	0.1187
21-07-2023	-0.0165	-0.0326	-0.1537	0.0131	-0.1145
22-07-2023	-0.0279	-0.0483	0.0582	-0.0617	0.1500
23-07-2023	0.0231	-0.0450	0.0115	-0.0280	0.0004
24-07-2023	0.0245	-0.0161	0.0388	-0.0128	0.0140
25-07-2023	-0.1332	-0.0890	-0.0076	0.1288	0.0119
26-07-2023	-0.0988	0.0486	-0.0875	-0.0206	-0.0400

27-07-2023	0.0389	0.0402	0.1758	0.0129	0.1344
28-07-2023	0.0960	0.0415	-0.0315	-0.0367	0.0097

In this portfolio optimization problem, we will assume an initial equal-weight allocation to the five stocks: TVS, Tata Steel, SBI, Infosys, and ICICI. The objective is to maximize the portfolio's expected return while maintaining a specific risk level.

Here is a step-by-step solution to the problem

Step 1: Data Preparation- Calculate the historical mean returns and the covariance matrix of returns for the five stocks based on the provided historical returns data.

Step 2: Define Parameters- Define a risk tolerance level or target portfolio volatility (e.g., you may specify a maximum acceptable annualized volatility, e.g., 15%). Specify the investment period (e.g., one month).

Step 3: Mean-Variance Optimization
Use a mean-variance optimization algorithm (e.g., the Markowitz model) to find the optimal portfolio allocation. The optimization seeks to maximize the portfolio's expected return while keeping the portfolio's risk (volatility) below the defined threshold.

Step 4: Solution Output
The optimization will provide the weights of each stock in the portfolio that maximize the expected return while controlling risk. These weights will add up to 100%. The solution will provide the optimal allocation, which specifies how much of your investment capital should be allocated to each of the five stocks.

Step 5: Portfolio Implementation
Implement the recommended portfolio allocation by allocating capital based on the calculated weights. For example, if the optimization suggests that 20% of your capital should be invested in TVS, allocate 20% to TVS stock.

Step 6: Ongoing Monitoring and Rebalancing

Monitor the portfolio's performance and rebalance the portfolio periodically (e.g., monthly, quarterly, or annually) to maintain the optimal allocation. Rebalancing is necessary as market conditions change and stock prices fluctuate.

Suppose the optimization provides the following optimal allocation:
TVS: 30%; Tata Steel: 20%; SBI: 10%' Infosys: 25%; ICICI: 15%

This means that, based on the historical returns and risk metrics, you should allocate 30% of your capital to TVS, 20% to Tata Steel, 10% to SBI, 25% to Infosys, and 15% to ICICI to maximize expected returns while managing risk. Please note that this is a simplified example. In practice, portfolio optimization can involve more sophisticated models, additional constraints, and other factors. Additionally, historical returns are just one input into the optimization process. Professional financial software and expertise are often used for portfolio optimization in real-world scenarios.there are few other scenarios author is trying to show in upcoming scenarios.

5.2 Numerical Problem 2- Machine Learning and Smart Beta Investing

Evaluate the performance of a portfolio consisting of Indian stocks and a benchmark (market return) using the CAPM (Capital Asset Pricing Model) approach. Here's a breakdown of each step in the code:

library(tidyquant)
library(tidyverse)

Step 1: Calculating Stock Returns

In this step, historical stock price data for four Indian stocks ("ICICIBANK.NS," "WIPRO.NS," "MARUTI.NS," and "TVSMOTOR.NS") is obtained from Yahoo Finance for the period from January 1, 2010, to December 31, 2015, and monthly returns are calculated.

The tq_get function retrieves the stock price data and tq_transmute calculates monthly returns.

The resulting data frame stock_returns contains columns for symbol and monthly returns (Ra) for each stock.

```
# Step 1: To calculate stock returns
stock_returns<- c("ICICIBANK.NS", "WIPRO.NS",
"MARUTI.NS","TVSMOTOR.NS") %>%
  tq_get(get  = "stock.prices",
      from = "2010-01-01",
      to   = "2015-12-31") %>%
  group_by(symbol) %>%
  tq_transmute(select     = adjusted,
          mutate_fun = periodReturn,
          period     = "monthly",
          col_rename = "Ra")
stock_returns
symbol      date           Ra
  <chr>      <date>        <dbl>
 1 ICICIBANK.NS 2010-01-29 -0.0561
 2 ICICIBANK.NS 2010-02-26  0.0503
 3 ICICIBANK.NS 2010-03-31  0.0921
 4 ICICIBANK.NS 2010-04-30 -0.000577
 5 ICICIBANK.NS 2010-05-31 -0.0879
 6 ICICIBANK.NS 2010-06-30  0.00706
 7 ICICIBANK.NS 2010-07-30  0.0501
 8 ICICIBANK.NS 2010-08-31  0.0805
 9 ICICIBANK.NS 2010-09-30  0.138
10 ICICIBANK.NS 2010-10-29  0.0450
```

Step 2: Creating a Portfolio

In this step, a portfolio is created by aggregating the returns of the four stocks. The portfolio is constructed with specific weights: 30% in "ICICIBANK.NS," 25% in "WIPRO.NS," 20% in "MARUTI.NS," and 25% in "TVSMOTOR.NS."

The tq_portfolio function is used to aggregate the returns based on the provided weights.

The resulting data frame portfolio_returns contains a column "Ra," representing the portfolio returns.

```
#Step 2: To create portfolio by aggregating stock returns
wts <- c(0.3, 0.25, 0.20, 0.25)
portfolio_returns<- stock_returns %>%
  tq_portfolio(assets_col  = symbol,
            returns_col = Ra,
            weights     = wts,
            col_rename  = "Ra")
portfolio_returns
  date           Ra
  <date>       <dbl>
 1 2010-01-29 -0.0415
 2 2010-02-26  0.0232
 3 2010-03-31  0.0769
 4 2010-04-30  0.0185
 5 2010-05-31 -0.00691
 6 2010-06-30  0.0682
 7 2010-07-30  0.0654
 8 2010-08-31  0.0309
 9 2010-09-30  0.0825
10 2010-10-29  0.0180
```

Step 3: Creating a Benchmark (Market Return)

This step retrieves the historical price data for the NIFTY 50 index (market return) from Yahoo Finance for the same time period (2010-2015).

Similar to Step 1, it calculates monthly returns for the market.
The market return data frame is plotted in red using the plot function.

```
#Step 3: To create benchmark (market return)
market_returns<- "^NSEI" %>%
  tq_get(get  = "stock.prices",
       from = "2010-01-01",
```

```
        to   = "2015-12-31") %>%
  tq_transmute(select     = adjusted,
               mutate_fun = periodReturn,
               period     = "monthly",
               col_rename = "Rb")
market_returns <- data.frame(market_returns)
plot(market_returns,type="l",col="Red",lty=1)
```

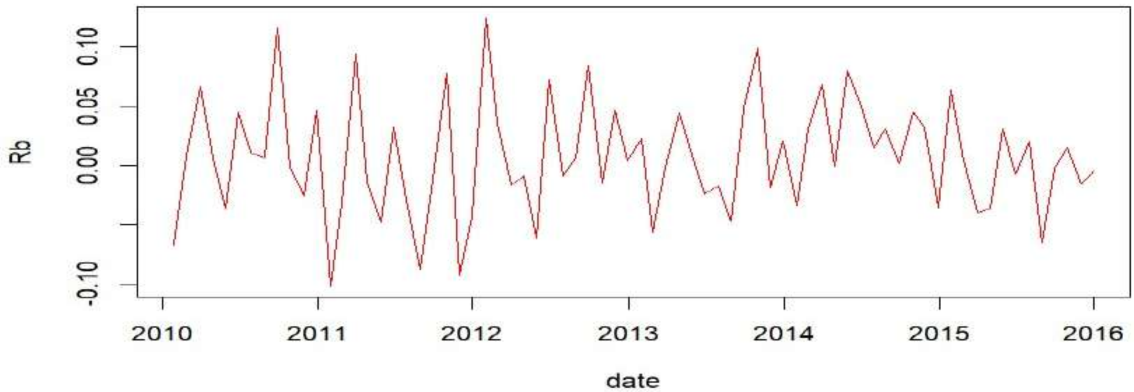

Figure 1: Return of stock over a period of time

Step 4: Combining Portfolio and Market Returns

Here, the portfolio returns and market returns data frames are combined based on the common "date" column.

```
#Step 4: TO combine portfolio and market return
merge_portfolio <- left_join(portfolio_returns,
                             market_returns,
                             by = "date")
merge_portfolio
date        Ra      Rb
  <date>     <dbl>   <dbl>
 1 2010-01-29 -0.0415  -0.0669
 2 2010-02-26  0.0232   0.00824
 3 2010-03-31  0.0769   0.0664
 4 2010-04-30  0.0185   0.00551
 5 2010-05-31 -0.00691 -0.0363
 6 2010-06-30  0.0682   0.0445
```

```
 7 2010-07-30  0.0654   0.0104
 8 2010-08-31  0.0309   0.00648
 9 2010-09-30  0.0825   0.116
10 2010-10-29  0.0180  -0.00203
```

```
tq_performance_fun_options()
$table.funs
 [1] "table.AnnualizedReturns" "table.Arbitrary"        "table.Autocorrelation"
 [4] "table.CAPM"              "table.CaptureRatios"    "table.Correlation"
 [7] "table.Distributions"     "table.DownsideRisk"     "table.DownsideRiskRatio"
[10] "table.DrawdownsRatio"    "table.HigherMoments"    "table.InformationRatio"
[13] "table.RollingPeriods"    "table.SFM"              "table.SpecificRisk"
[16] "table.Stats"             "table.TrailingPeriods"  "table.UpDownRatios"
[19] "table.Variability"

$CAPM.funs
 [1] "CAPM.alpha"       "CAPM.beta"        "CAPM.beta.bear"   "CAPM.beta.bull"
 [5] "CAPM.CML"         "CAPM.CML.slope"   "CAPM.dynamic"     "CAPM.epsilon"
 [9] "CAPM.jensenAlpha" "CAPM.RiskPremium" "CAPM.SML.slope"   "TimingRatio"
[13] "MarketTiming"
$SFM.funs
[1] "SFM.alpha"       "SFM.beta"        "SFM.CML"         "SFM.CML.slope"   "SFM.dynamic"
[6] "SFM.epsilon"     "SFM.jensenAlpha"
$descriptive.funs
[1] "mean"           "sd"             "min"            "max"            "cor"
[6] "mean.geometric" "mean.stderr"    "mean.LCL"       "mean.UCL"
$annualized.funs
[1] "Return.annualized"        "Return.annualized.excess" "sd.annualized"
[4] "SharpeRatio.annualized"
```

```
$VaR.funs
[1] "VaR"  "ES"   "ETL"  "CDD"  "CVaR"
$moment.funs
 [1] "var"              "cov"              "skewness"         "kurtosis"
 [5] "CoVariance"       "CoSkewness"       "CoSkewnessMatrix" "CoKurtosis"
 [9] "CoKurtosisMatrix" "M3.MM"            "M4.MM"            "BetaCoVariance"
[13] "BetaCoSkewness"   "BetaCoKurtosis"
$drawdown.funs
[1] "AverageDrawdown"   "AverageLength"     "AverageRecovery"   "DrawdownDeviation"
[5] "DrawdownPeak"      "maxDrawdown"
$Bacon.risk.funs
[1] "MeanAbsoluteDeviation" "Frequency"             "SharpeRatio"
[4] "MSquared"              "MSquaredExcess"        "HurstIndex"
$Bacon.regression.funs
 [1] "CAPM.alpha"        "CAPM.beta"         "CAPM.epsilon"      "CAPM.jensenAlpha"
 [5] "SystematicRisk"    "SpecificRisk"      "TotalRisk"         "TreynorRatio"
 [9] "AppraisalRatio"    "FamaBeta"          "Selectivity"       "NetSelectivity"
$Bacon.relative.risk.funs
[1] "ActivePremium"    "ActiveReturn"     "TrackingError"    "InformationRatio"
$Bacon.drawdown.funs
[1] "PainIndex"     "PainRatio"     "CalmarRatio"   "SterlingRatio" "BurkeRatio"
[6] "MartinRatio"   "UlcerIndex"
$Bacon.downside.risk.funs
 [1] "DownsideDeviation"     "DownsidePotential"     "DownsideFrequency"
 [4] "SemiDeviation"         "SemiVariance"          "UpsideRisk"
 [7] "UpsidePotentialRatio"  "UpsideFrequency"       "BernardoLedoitRatio"
[10] "DRatio"                "Omega"                 "OmegaSharpeRatio"
[13] "OmegaExcessReturn"     "SortinoRatio"          "M2Sortino"
[16] "Kappa"                 "VolatilitySkewness"    "AdjustedSharpeRatio"
[19] "SkewnessKurtosisRatio" "ProspectRatio"
$misc.funs
```

```
[1] "KellyRatio"   "Modigliani"   "UpDownRatios"
```

Step 5: Evaluating Portfolio Performance

The code uses the tq_performance function to evaluate portfolio performance using the Capital Asset Pricing Model (CAPM). The CAPM is a widely used model to estimate the expected return of an asset or portfolio based on its risk and the risk-free rate.

The result is stored in the performance_evaluation data frame.
Finally, the results are saved to a CSV file named "performance_evaluation.csv."

```
# Step 5: To evaluate the portfolio performance
performance_evaluation <-merge_portfolio %>%
ActivePremium   Alpha AnnualizedAlpha   Beta `Beta-` `Beta+` Correlation `Correlationp-value`
      <dbl>   <dbl>             <dbl>  <dbl>    <dbl>    <dbl>         <dbl>
<dbl>
1       0.179 0.0129          0.167  1.24    1.25    1.18      0.761               0

  tq_performance(Ra = Ra,
             Rb = Rb,
             performance_fun = table.CAPM)
performance_evaluation
write.csv(performance_evaluation,"performance_evaluation.csv",
       row.names ="my_portfolio")
```

5.3 Numerical Problem 3- R based solution for Portfolio optimisation

Problem Definition: The problem involves optimizing a portfolio of financial assets with the following objectives: Maximize the portfolio's expected return. Minimize the portfolio's risk (standard deviation). The portfolio must adhere to the following constraints: Full investment: The entire investment should be allocated to the assets in the portfolio. Long-only: The portfolio should consist of long positions only; no short positions are allowed.

Code solution and Explanation:

```
library(PortfolioAnalytics)
library(quantmod)
```

The code begins by reading financial data from a CSV file named "Portfolio Optimisation .csv." The data is loaded and converted into an xts (time series) object.

```
data <- read.csv("Portfolio Optimisation .csv",header=TRUE)
data_ts <- ts(data)
data_xts <- as.xts(data_ts)
str(data_xts)
data_port <- data_xts[,2:6]
```

A specific subset of the data is extracted and assigned to the data_port variable. This subset includes columns 2 to 6, which represent the returns of different financial assets.

```
str(data_port)
```

The chart.CumReturns function is used to plot the cumulative returns of the selected financial assets.

```
chart.CumReturns(data_port,main="Cumulative Returns",
            legend.loc ="topleft",geometric = TRUE )
```

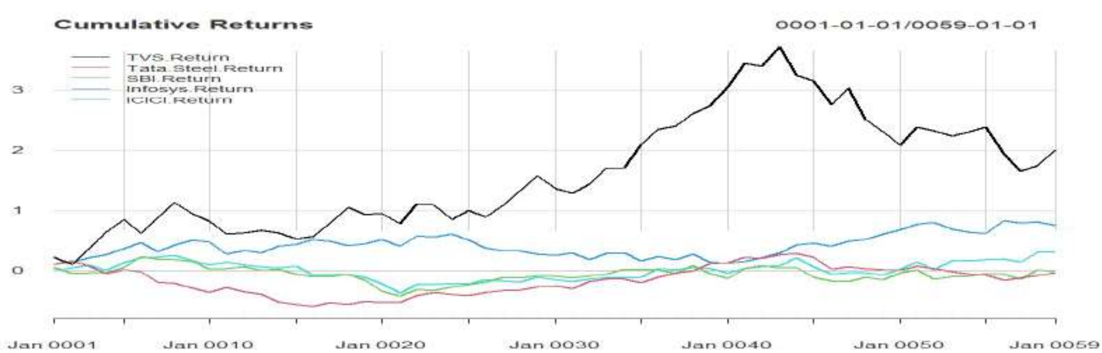

Figure 2: cumulative returns of selected stocks

A portfolio specification named my_portfolio is created. This portfolio is used to define constraints and objectives for the optimization.

Constraints are added to the portfolio using the add.constraint function. Two constraints are added: full investment (the entire investment should be used) and long-only (no short positions).

Objectives are added to the portfolio using the add.objective function. Two objectives are added: maximizing the mean return (expected return) and minimizing the standard deviation (risk).

```
my_portfolio <- portfolio.spec(colnames(data_port))
my_portfolio <- add.constraint(portfolio =my_portfolio,
                    type = "full_investment")
my_portfolio <- add.constraint(portfolio =my_portfolio,
                    type = "long_only")

my_portfolio <- add.objective(portfolio =my_portfolio,
                    type = "return",name = "mean")
my_portfolio<- add.objective(portfolio =my_portfolio,
                    type = "risk",name = "StdDev")
print(my_portfolio)
```

The opt <- optimize.portfolio function is used to optimize the portfolio based on the defined constraints and objectives. The optimization method used here is "random."

The code then creates a risk-reward chart using the chart.RiskReward function, plotting the risk (standard deviation) against the return (mean).

```
opt <- optimize.portfolio(data_port,portfolio = my_portfolio,
                optimize_method ="random",trace=TRUE)
chart.RiskReward(opt,risk.col = "StdDev",return.col="mean",chart.assets
=TRUE)
```

Portfolio optimization results, including weights assigned to each asset, are printed using the print(opt) and extractWeights(opt) functions.

```
print(opt)
extractWeights(opt)
```

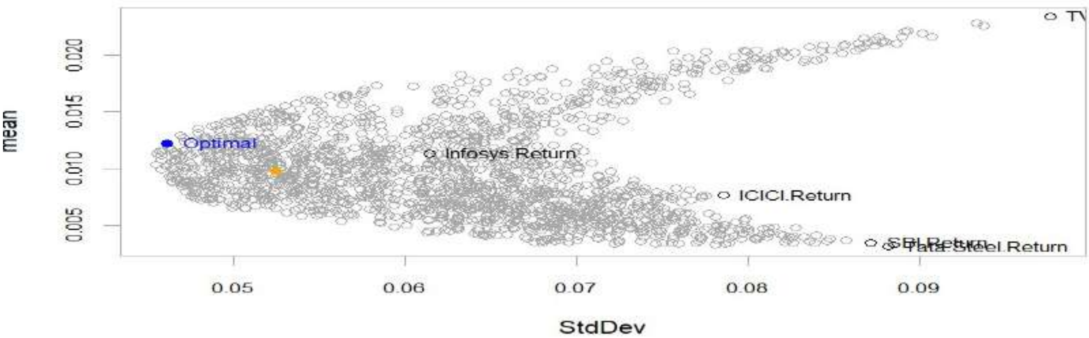

Figure 3: optimised portfolio using Markowitz approach

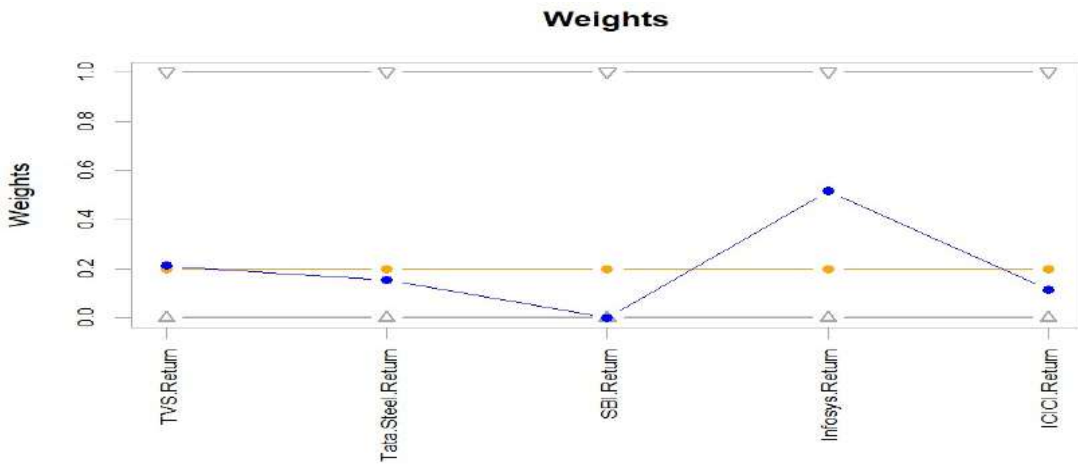

Figure 4: weight allocations across various stocks

Weight allocation for each asset in the optimized portfolio is displayed in a chart using the chart.Weights function.

Efficient frontier analysis is performed using the create.EfficientFrontier function. A set of efficient portfolios is generated based on different combinations of risk and return.

```
chart.Weights(opt)
chart.EF.Weights(opt,match.col="StdDev")
efficient_options <- create.EfficientFrontier(data_port, portfolio=my_portfolio,
        n.portfolios = 20,match.col="mean",type ="random",search_size = 1500)
```

A summary of the efficient frontier options is provided using the summary(efficient_options) function.

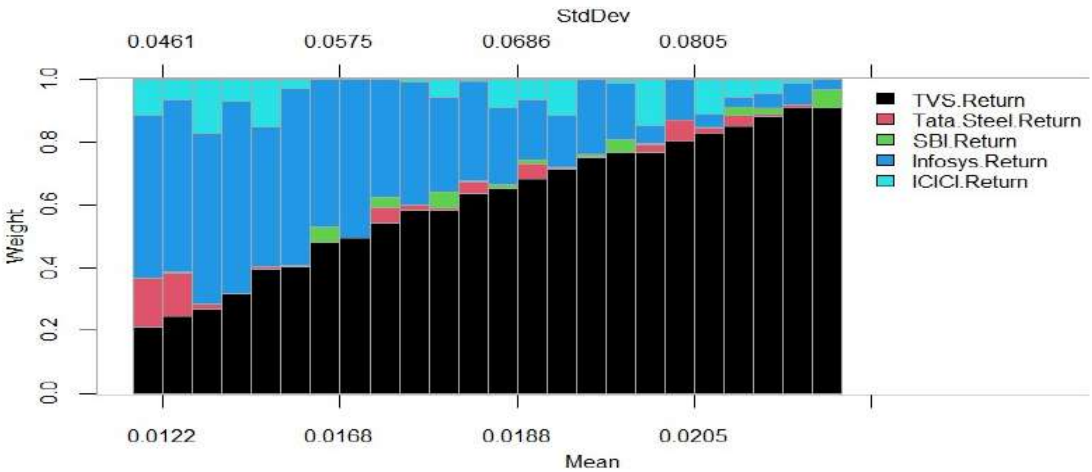

Figure 5: optimised portfolio weight allocation

summary(efficient_options,digits=4)

In summary, the problem involves optimizing a financial portfolio with specific constraints and objectives to maximize return and minimize risk. The code utilizes PortfolioAnalytics functions to perform this optimization and provides visualizations of the results, including efficient frontier analysis.

5. **Future of Smart Beta Investing in Machine Learning**

The future of smart beta investing, underpinned by the integration of machine learning, promises a landscape of remarkable transformation and innovation. Advanced machine learning models will empower investors to harness complex, non-linear patterns in data, enhancing factor selection, risk management, and predictive analytics within smart beta strategies. Real-time data integration, facilitated by machine learning, will enable strategies to adapt swiftly to evolving market conditions by leveraging dynamic information sources like social media sentiment and news feeds(Jang-Jaccard & Nepal, 2014). Moreover, the utilization of alternative data sources, from satellite imagery to unconventional financial indicators, will become more sophisticated, expanding the toolbox available to smart beta investors. Machine learning will facilitate dynamic portfolio management, continuously optimizing allocations based on shifting market dynamics and risk factors(Roy et al., 2015). Additionally, advanced risk management will be a focal point, with precise assessments of market volatility and tail risk events, allowing for proactive portfolio protection during turbulent times. Machine learning will pave the way for personalized smart beta strategies, tailoring factors and constraints to align with individual investor preferences, risk tolerance, and financial goals. The integration of Environmental, Social, and Governance (ESG) considerations and the development of thematic strategies will gain prominence, reflecting investor priorities(Alessandrini & Jondeau, 2020). As these strategies continue to evolve, education and awareness initiatives will play an essential role in helping investors grasp the complexities and potential benefits of machine learning-driven smart beta investing. Ultimately, the future of smart beta investing using machine learning is poised to provide investors with advanced tools to optimize their portfolios, manage risk, and align their investments with their values and preferences, driving innovation and transformation in the financial markets.

6. Conclusion

In conclusion, the integration of machine learning into the realm of smart beta investing represents a significant and transformative evolution in the field. The traditional methods of smart beta investing, while widely practiced, face inherent challenges in adapting to dynamic market conditions and making the most of real-time data. These methods, relying heavily on historical financial metrics and past market data, can lag behind in capturing emerging trends and shifts in market sentiment. Furthermore, they may overfit historical data and assume that historical relationships between factors and asset performance will persist indefinitely. The potential for crowded trades and model instability can further hinder the effectiveness of these traditional strategies.

Machine learning has stepped in to address these challenges by offering adaptability, real-time insights, and the capability to navigate changing market dynamics more effectively. It has introduced several applications, such as advanced factor selection, robust risk management, predictive analytics, dynamic portfolio allocation, and thorough backtesting. These applications leverage vast amounts of data, discover non-linear patterns, and adapt to changing market conditions.

The adoption of machine learning in smart beta investing is not limited to any particular region. Countries around the world, from the United States to Europe and emerging markets, are embracing these technologies to enhance their investment strategies. These applications provide an edge in capturing market opportunities, managing risk, and achieving higher risk-adjusted returns. The numerical evidence presented in the chapter illustrates the potential for machine learning to optimize portfolio allocation, balancing expected returns and maintaining specific risk levels. Machine learning can offer insights into portfolio composition that can potentially outperform traditional methods.

In summary, the incorporation of machine learning in smart beta investing has propelled this investment approach into a new era of adaptability, predictive power, and real-time data integration. The future of smart beta investing is increasingly intertwined with machine learning, offering investors a sophisticated set of tools to navigate the complexities of modern financial markets. As the field continues to evolve, investors who harness the power of data and advanced algorithms are poised to stay competitive and achieve superior financial outcomes in an ever-changing investment landscape.

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Chapter-9

ADDING MACHINE LEARNING EDGE TO SMART BETA INVESTING

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1 Introduction

Smart-beta strategies are systematic investing innovations (Harvey, 2021). Some essential attributes usually associated with these strategies are low cost, deployment of formula-based or algorithm-based strategies that offer successful signals when backtested, made available to investors through an index, and access through an ETF or mutual funds.

The attributes of smart-beta investing strategies, especially the need for systematic investing, make them amenable to applying machine learning tools. However, the use of machine learning tools is optional. The success of machine learning algorithms in areas outside finance, for example, voice recognition (Siri), image recognition (Tesla-self driving), and recommendation engines (ecommerce-Amazon), should be explored in all areas of finance. Machine learning has mainly made a mark in classification tasks. Recently, a machine learning algorithm, AlphaZero, taught itself to be a chess master by playing against itself for four hours.

This chapter examines evidence from the literature about the reported use of machine learning (ML) in smart beta investing. Second, evaluate the current application in the industry reported by asset managers and investors. Third, under which roles and usage does machine learning offer an edge in building smart-beta portfolios?

The potential application of machine learning in building portfolios and portfolio optimization is related to the widespread availability of these tools, strong computing power (including cloud computing) and low-cost storage. The tools are available in open source and not necessarily behind firewalled industrial software providers. Open source enables faster deployment, evaluation and development of the tools. Unfortunately, we may not know the remarkable achievements, sophistication and capability of private or proprietary tools.

This chapter is structured as follows. Section 2 explores the insights from academic literature and industry applications. Next, section 3 follows with a general overview of ML techniques for 'Smart Beta', and Section 4 discusses a few specific ML applications in smart beta investing. Section 5 illustrates an empirical example of smart beta investing. We conclude in section 6 with concluding remarks and a discussion on the issues and challenges of using ML in smart beta investing.

2 Machine Learning in Smart Beta Investing

2.1 Insights from Academic Literature

Martínez and Manuel (2017) employed the 'Random Forest' algorithm in their research, incorporating momentum, earnings yield, Dividend yield, volatility, and net debt. Their empirical findings indicated a Sharpe ratio of 0.1233 for a high smart-beta portfolio compared to -0.1763 for a low smart-beta portfolio. In the study by Maguire et al. (2018), machine learning and smart-beta strategies are combined for portfolio optimization. They utilized an adaptive boosting classifier with a suite of momentum indicators to construct a smart beta portfolio, which was then hedged to achieve a beta-neutral portfolio.

Lu et al. (2019) integrated various factors using neural networks, machine learning, and deep learning to delve deeper into the insights about portfolio returns. Their research revealed that the index created based on these insights displayed enhanced stability and profitability.

Heaton et al. (2017) utilized deep learning hierarchical algorithms to illustrate the development of a 'smart' index. Krkoska and Schenk-Hoppé (2019) pointed out that conventional statistical methods may not effectively detect herding risk in factor products, and innovative techniques are needed to identify and address the issues related to herding behaviour.

Simoes (2022) applied an algorithm combining Modern Portfolio Theory with two machine learning algorithms, K-means Clustering and Random Forest. They apply the algorithm to predict the macroeconomic state and determine the optimal 'tactical' portfolio allocation for each security over the investment period.

Machine learning can uncover nonlinear and interaction effects (Blitz, 2023) and offer performance improvements compared to traditional methods using the same dataset (Gu et al., 2020). Leung et al. (2021) also emphasized the challenge of excessive turnover associated with ML models due to their reliance on short-period forecasts, highlighting a key difference with traditional linear models less constrained by such limitations, such as gradient boosting machines.

2.2 Industry Applications and Innovations
BlackRock's Utilization of AI and ML

Blackrock asset management believes that Artificial Intelligence (AI) and ML can help improve outcomes[1] in asset management. They report using technology in several aspects of the investment process, including "the data and research processes that drive the creation of alpha signals and models,

[1] https://www.blackrock.com/corporate/literature/whitepaper/viewpoint-artificial-intelligence-machine-learning-asset-management-october-2019.pdf

pre-trade analysis, and understanding investment risks in a given portfolio." The use of ML in Smart beta portfolios is primarily to tweak allocations within an index to favour investment characteristics like "sustainable dividends or low volatility".

Robeco and Aberdeen's Portfolio Optimization

Robecco and Aberdeen asset management have reported using machine learning for portfolio selection and optimization. Aberdeen has used algorithms such as support vector machines, classification trees and neural networks. The different algorithms can give the same trading decisions and help develop confidence in the trading tools. They report reduced processing time by using ML tools together with cloud

Rayliant's Innovative Approach

Robecco and Aberdeen asset management have reported using machine learning for portfolio selection and optimization. Aberdeen has used algorithms such as support vector machines, classification trees and neural networks. The different algorithms can give the same trading decisions and help develop confidence in the trading tools. They report reduced processing time by using ML tools together with cloud

State Street Fund Managers

Ung, Chawla and Miklaszewski from State Street global advisors argue in their case study[2] that smart-beta strategies are beneficial to achieve diversification from market beta in long-only equity allocations. The second way to attempt outperformance is timing allocations across smart-beta strategies. They evaluate hierarchical clustering techniques from machine learning in multi-factor smart-beta allocation.

3 Machine Learning Techniques for Smart Beta

Martínez & Manuel (2017) refer to machine learning as "advanced techniques of statistics". The role of smart beta is to extract factor premium. Portfolio

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[2] https://www.ssga.com/ie/en_gb/institutional/etfs/insights/machine-learning-smart-beta-case-study

profitability depends on exposure to fundamental value, momentum, quality and low-risk factors. A risk factor premium can be explained either based on a premium to investors who expose themselves to additional risk or as behavioural bias-related exposure due to the errors of the investors. The authors prefer the former explanation.

The role of machine learning is to build a new factor that combines the potentially positive characteristics of any of the factors or a combination of them to capture the strengths of the factors and reduce its weaknesses in a dynamic portfolio. Such a dynamic portfolio should maximize the average expected performance and minimize annualized volatility..

3.1 Machine Learning Techniques used for Smart Beta (Martínez & Manuel (2017)

Machine Learning Techniques Used for Smart Beta (Martínez & Manuel (2017) Machine learning, considered a subset of 'artificial intelligence', refers to the automated detection of meaningful patterns in data. The statistical technique, mathematical formula or methods attempt to convert available results of outcomes into knowledge. A subset of data is input into the learning algorithm as training data and the output is expertise or pattern—feedback-based learning. The fundamental pillars of any learning system are the inputs, outputs and algorithms. The input is in the form of an attribute vector called "instances". These attributes can take values within any finite set, real values within a finite or infinite set.

The type of output differentiates the types of learning:

1. Supervised learning: This algorithm creates a function that relates the output and input variables. Regression, Decision Tree, Random Forest, KNN, and Logistic Regression are widely used supervised learning algorithms.

2. Unsupervised learning: There is no input category information, and it is treated as random variables. The algorithm seeks to achieve groupings of the population in different groups. The algorithm uses a

density model to recognize patterns to label the new inputs. The widely used non-supervised learning algorithms are the Apriori algorithm K-means.

3. Reinforcement Learning: The algorithm is trained to make specific decisions. Models like this train itself continually using trial and error. Example of Reinforcement Learning: Markov Decision Process.

3.2 Machine Learning and Stock Selection

The relevance of quantitative factor models depends on the factors' relevance. These may change over time. Investors attempt to master this by using dynamic models that learn from past data. Traditionally, investors have used economic techniques such as regression-based analysis. The inherent noise in financial data can lead to exciting challenges (Asness, 2016). Factors may be correlated, leading to multicollinearity in multi-factor models; factors and returns relationship may be time-varying and nonlinear.

Rasekhschaffe and Jones (2019) identify overfitting as the key challenge in developing machine-learning models for stock selection. In order to use machine learning to forecast the cross-section of stock returns, they list out two strategies to overcome this challenge. These are forecast combinations and feature engineering.

Forecast Combinations

The intuition behind forecast combinations is to use multiple forecasts and average them out rather than attempting to achieve the best result. Successful machine learning algorithms are ensemble algorithms that rely on bootstrap aggregation (bagging), i.e. averaging forecasts from different training sets or boosting, i.e. re-weighting observations to put more weight on misclassification on prior rounds. 'Random forests' is an example of bagging, and 'Adaboost' is an example of boosting. Rasekhschaffe and Jones (2019) recommend combining forecasts from different classes of algorithms, adding forecasts from different training data subsets, adding different factor libraries and forecasting for different horizons.

Feature Engineering

Feature engineering employs our domain knowledge to the job. Find out which problems we ask the ML to solve and which algorithms we deploy. In the context of stock selection, this means asking the following questions:

Goal: What are we trying to forecast?

Tool: Given the goal, which algorithms are most suitable?

Training: Which training windows will likely be most informative or better represent the market events?

Conditioning: How can we standardize factors and returns?

Smart Beta: Which factors are likely to provide valuable information?

4 Applications of Machine Learning in Smart Beta Investing

4.1 Hidden Markov Models in Smart Beta

Fons (2022), Lund-Jensen (2021) and Fons et al. (2021) discuss and present applications of the use of Hidden Markov Models (HMM) in smart beta investing. Hidden Markov models are classified as Regime switching models. Regime-switching models are a class of parametric nonlinear time series models with applications in several fields, such as engineering, economics, finance and many others. In a regime-switching model, the parameters can change over time according to an underlying state process, such as a finite-state hidden Markov chain.

HMM is a type of Markov switching model and finds application in economics and finance (Guidolin, 2011). They can simultaneously capture known characteristics of financial time series (such as time-varying correlations, skewness and kurtosis) and unknown processes underlying the financial return series. It is natural to have regimes in financial economics where different regimes are related to the outcomes.

Ma et al. (2011) deploy a regime-switching model with three states to study time-varying risk premiums. Peixin et al. (2011) train the regime-switching models with six well-established factors found in the literature, and the assets used for allocation are nine sector ETFs (Exchange Traded Funds). These early models were straightforward and dealt with a single asset to discover - buy, sell and hold calls based on the regimes. Fons (2022) illustrates an example of such an approach in the context of smart beta. A HMM trained with the returns of three factors (Value, Quality and Momentum). The hidden states are identified separately for each of the three factors, and the returns are predicted. In Fons et al. (2021), the basic HMM is extended by adding features. Features whose distribution is related to the hidden states are considered relevant, and features whose distribution is not related to the hidden state are independent. This enhanced HMM finds application in a dynamic asset allocation system for smart-beta investing.

The role of the ML (HMM) is to detect market regimes and smart-beta behaviour within the regime. The varied styles of smart-beta strategies are based on different groups of factors. Factors across groups have a lower correlation than factors within groups. For example, a macroeconomic expansion environment may be conducive to a momentum investment strategy but not quality. HMM can address this requirement by building multi-factor investments where the factors do not act against each other depending on the environment. Further, the same knowledge can be used for factor rotation.

4.2 Hierarchial risk clustered algorithm

De Prado (2016) proposed a hierarchical risk clustered algorithm using graph theory and unsupervised machine learning to build a diversified portfolio. This approach is claimed to be less sensitive to changes in expected returns when using the classical Markowitz mean-variance optimization to build portfolios. The other approaches practitioners use to deal with this challenge are algorithms, such as equal risk contribution or maximum decorrelation, to allocate portfolios. However, All such approaches require a well-conditioned covariance matrix to ensure that the solutions generated do not become too sensitive to small changes in the input data. Estimation errors will offset diversification benefits if the investments are correlated. Estimation errors lead to poor out-of-sample performance. Raffinot (2017) and Raffinot (2018) further adapted the risk clustering algorithm. The main steps for this adapted approach are:

1) "tree clustering by selecting the optimal number of clusters. The algorithm segregates the assets into different clusters based on a similarity measure (risk or correlation) and clustering". State Street implementation uses the Ward linkage[3] which is based on variances.

2) "top-down recursive bisection and assignment of weights to each of the assets in the portfolio." State Street managers first compute the weights for each cluster. The cluster weights are adjusted by an alpha factor that reflects the ratio of similarity measure between the two clusters. Then, the individual asset weights within each cluster are calculated.

They report that the hierarchical clustered smart-beta portfolio achieved a higher level of risk reduction than the equally weighted portfolio. The metrics of diversification are not compromised in the process.

4.3 Enhanced index replication

Given the popularity and emphasis on passive investing, investing strategy could improve index replication based on Smart Beta. This attempt at an index-plus portfolio is the antithesis of passive investing. Korzen and Slepaczuk (2021) argue that investors (institutions and individuals) find it challenging to replicate the index due to higher trading costs. High momentum factors on individual stocks induce higher trading costs. They offer a solution to limit the number of assets used for replication but remain within tracking error limits. Their primary approach is to apply the Smart Beta methods to decrease the adverse risk associated with the returns of index replication. Given the better performance of dynamic time-warping algorithms, the authors suggest that sequential pattern recognition methods among machine learning algorithms may have potential applications

[3] The Ward linkage method minimises the increase in the sum of squared error when two clusters are joined.

5 Empirical Examples and Performance Evaluation

In this section, we aim to provide a minimal example for illustration without the detailed technical complexity of implementing an ML model for smart-beta investing. We start with assets categorized by three Indices from India. The Nifty Indices - Nifty50, Nifty Midcap100 and Nifty Smallcap100 are offered as a part of the global major, S&P's portfolio and NSE exchange based in Mumbai, India. The three indices chosen are diversified portfolios and do not have any overlap in securities. Investors could invest in such asset classes through ETFs or Index mutual funds. These portfolios by themselves are smart-beta portfolios based on market capitalization float. We assume that investor's preference is to consider passive investing and not active investing. Such an investor would consider the return and risk associated with such asset classes before choosing the investment; alternatively, before the investor invests in all three based on a specific asset allocation.

Dataset:

Our data set is the index prices from 1 October 2010 to 29 September 2023. For sections 6.1 to 6.5, refer to the comparative performance summary in Table 1 and for the use of ML in smart beta given in section 6.6, refer to the summary in Table 2 and Table 3.

5.1 Option 1: Buy and hold for long durations

Table 1: Comparative Summary of Options

Option	Avg Return (%)	Standard Deviation	Sharpe Ratio
Buy and Hold	10.87	0.17	20.03
Rebalance	11.85	0.22	20.03
Asset Allocation	12.49	0.2345	21.72
Smart-Beta Growth	13.25	0.234	25.014
Smart-Beta Value	12.57	0.2587	19.97

If the investor needs to choose one asset, it is the Nifty Midcap100 based on the superior Sharpe Ratio. The risk-free rate considered is 7.4%. The risk-adjusted returns or average returns and standard deviation of returns can vary greatly based on when the investor entered during the entire period. The buy and hold strategy over the period 2014-2023 delivers a Sharpe ratio ranging from 150 to -64, depending on different months of entry. Hence, investors may prefer rebalancing across asset classes to improve risk-adjusted returns further.

5..2 Option 2: Rebalance across asset classes based on a signal

Since investors also prefer diversified portfolios and past returns do not guarantee future returns, investors may want to invest in all three assets using a portfolio approach and rebalance based on some criteria after a periodic portfolio review. We introduce rebalancing after every quarter. The past data of 5 years is used to evaluate the Sharpe ratio, and the investment is made on the asset class offering the best Sharpe ratio. The portfolio chooses to invest in either of the three asset classes from October 2014 to July 2023 but marginally underperforms. This strategy can offer Rebalancing costs that are ignored.

5.3 Option 3: Asset allocation across three asset classes

This approach allocates assets to the highest-ranked asset classes based on a five-year Sharpe Ratio. This allocation strategy offers the best risk-adjusted returns. The allocation to the highest-ranked asset is 50 percent, followed by 30 percent and 20 percent.

Smart-Beta Investing

While ML can be used for smart-beta investing, in our experiments, we start with building smart-beta portfolios in synthetic indices and then use ML to stitch the smart-beta portfolios into the investor portfolio. One of the features of smart-beta investing is relatively lower turnover. However, we have yet to adhere to this in the initial growth and value smart-beta portfolios or in the later example to illustrate the ML application where we do monthly rebalancing.

At each monthly portfolio review, we rank the assets based on the style factor - growth or value. The investor would prefer to allocate more to an undervalued asset (Although alternate investor strategies exist where a different decision may result). The allocation to the highest-ranked asset is 20 percent, followed by 30 percent and 50 percent. i.e., for example, the highest P/E or P/B asset is allocated 20 percent.

5.4 Option 4: Smart-Beta Growth Portfolio based on P/E ratio of the three starting indices (Asset classes)

5.5 Option 5: Smart-Beta Value Portfolio based on P/BV ratio of the three starting indices (Asset classes)

At this stage, the Smart beta growth portfolio emerges as a better strategy offering superior risk-adjusted returns. Surprisingly, the smart-beta value portfolio has marginally lower returns but a higher standard deviation and loses out.

5.6 Option 6: Use ML to choose the smart-beta strategies

ML can be deployed to build smart-beta portfolios in the first place. We avoid it as smart-beta indices are currently available and can be used directly. However, if the investor must combine assets using themes for which indices are unavailable, then they could attempt using ML.

We select an application of ML that may not be easy to replicate otherwise. Is it necessary for investors to choose between Smart-beta growth or value strategies? Alternatively, can the investor switch between the two based on specific triggers?

We want to use the Hidden Markov Model to identify any underlying states related to growth or value portfolio returns. The portfolio could switch between growth and value smart-beta strategy by identifying such hidden states. We consider a model with two states and a Gaussian HMM. Our data has returns for 3222 days. We use a moving window to train the ML model using 1000 daily returns and then predict/forecast the future returns. Based on the hidden states identified by the ML model, it chooses between the value and growth strategies. The performance is tested against out-of-sample returns for ten trading days and reported. We have ignored the number and frequency of rebalancing as we have not considered portfolio-rebalancing costs. Portfolio rebalancing costs could be another criterion or constraint that should be a criterion in evaluating the strategy.

Figure 1: Predicted States vs Actual Returns

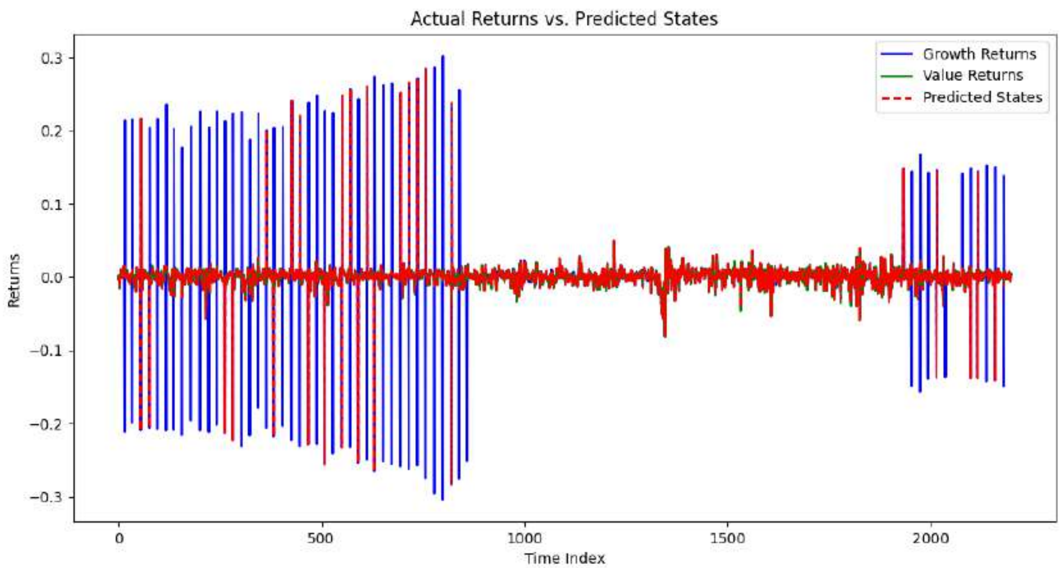


Figure 1 gives the predicted states and the returns. The HMM generally begins to get the prediction right in a lower volatility period from the testing time index of 850 to 1950.

The changes in the predicted states over time are given in Figure 2. Figure 3 compares the performance of the ML model prediction with the growth and value smart-beta portfolios. The outperformance of the predicted portfolio is clearly given in this trial. Nevertheless, several instances exist where the ML model gets the prediction or relationship between the hidden state and the returns from the smart-beta portfolios wrong. We emphasize that the HMM is a probability-based tool, so its output should be inferred in that light. In order to evaluate overall performance, one approach is to conduct a Monte Carlo simulation of the model results.

Figure 2: Predicted States by the Hidden Markov Model

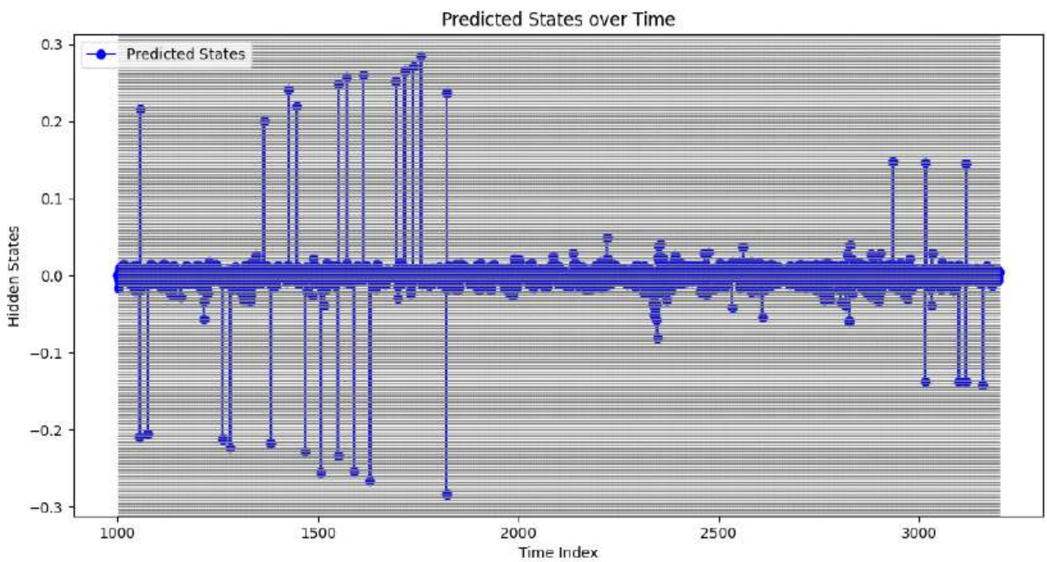


Figure 4 gives a comparison of the actual versus the predicted returns. A number of predicted returns are incorrect in out-of-sample performance evaluations.

Table 2: Hidden Markov Model Performance

Performance Metrics	Results
Mean Absolute Percentage Error	2.22
Mean Squared Error	0.0015
Sharpe Ratio (Predicted Returns)	31.18
Sortino Ratio (Predicted Returns)	0.176
Sharpe Ratio (Growth Returns)	17.32
Sortino Ratio (Growth Returns)	0.0997
Sharpe Ratio (Value Returns)	86.78
Sortino Ratio (Value Returns)	0.505

Figure 3: A trial showing outperformance of ML based strategy Cumulative portfolio returns

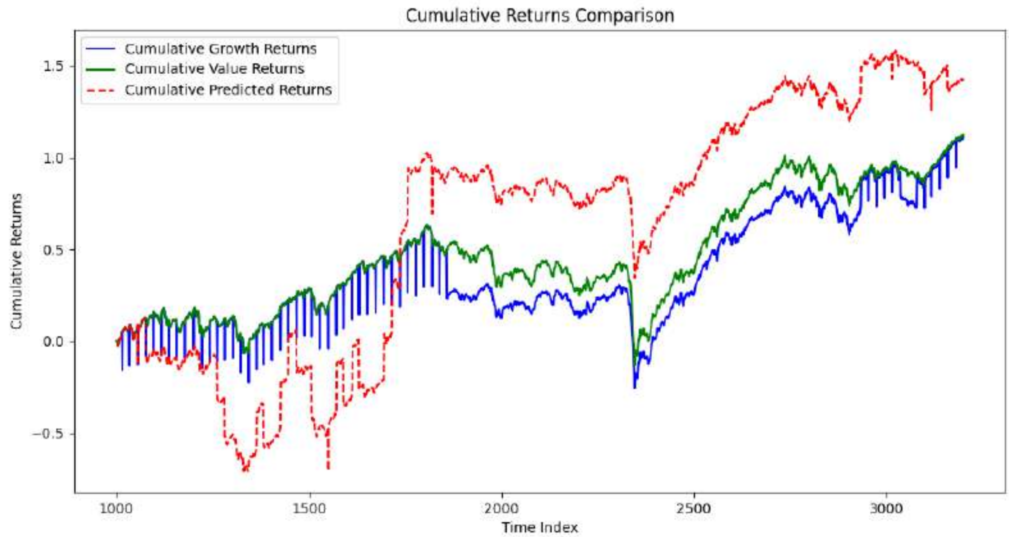
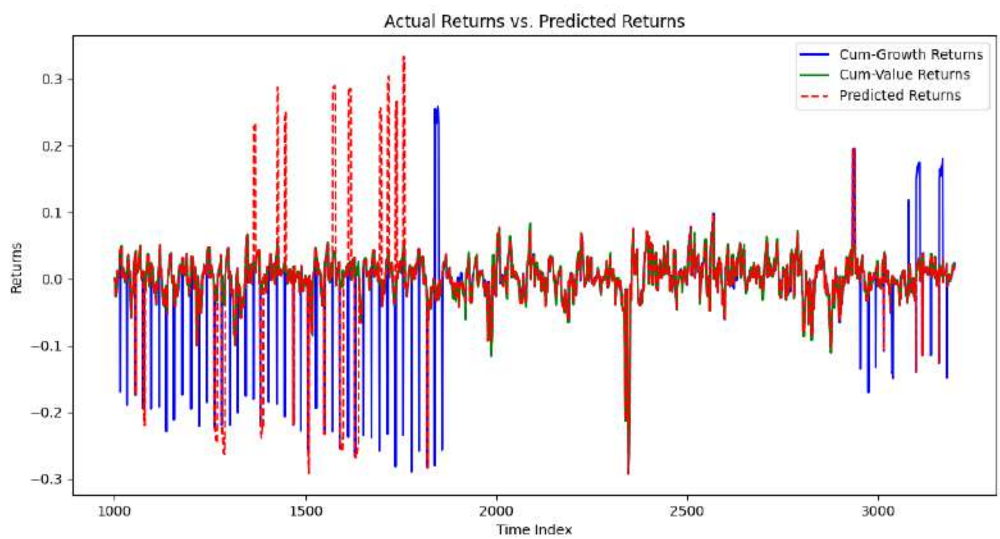


Figure 4: Actual vs predicted returns over time



Since the performance of the ML models is path-dependent, we conduct a Monte Carlo simulation of the model and report the averages from 1000 trials

Monte-carlo simulation

Table 3: Monte-Carlo Simulation Results

Performance Evaluation based on 1000 trials, prediction for 5 trading days	**Results**
Sharpe Ratio (Predicted Returns)	0.12
Standard Deviation of Sharpe Ratio	0.26

7 Conclusion

The black-box element related generally to the use of lesser-known but effective ML and AI tools still exists for want of further information sharing by industry participants.

Some challenges related to ML and smart beta emanate from systematic approaches. Systematic strategies may take time to adapt to structural changes in the market. They also present the risk of "tech-washing", whereby an investment product claims to use "the latest machine learning tools," but the tools are misapplied or play a minimal role. Importantly, when an inexperienced researcher applies systematic tools, the backtests are often overfit, leading to disappointing performance in live trading. (Harvey, 2021). As we illustrate in the example in section 5, there remains a high potential to misinterpret and misreport the results of a machine learning-based smart-beta strategy.

The feedback[4] from China-based asset managers who have been employing several AI tools in investing is that the regulatory burden of compliance is overarching. The fund managers of fintech describe some AI-powered models as 'black boxes' or 'unexplainable' from the perspective of being able to communicate the decision-making process from a compliance perspective. Reuters quotes Peter Shepard, managing director of MSCI Research, who says that AI provides scale to asset managers and not necessarily intelligence.

[4] https://www.reuters.com/world/china/china-fund-managers-embrace-robots-competition-intensifies-2021-05-21/

Hence, their role would continue to unlock 'new, alternative and unstructured data sets' and transform the investment process.

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