Don't Judge a Book by its Cover: Evidence of Returns Based Factor Exposures of Multifactor Strategies in India

Rajan Raju* Joshy Jacob†‡

June 2024

Abstract

The number of funds that employ smart beta strategies to generate higher returns for investors has grown in India in recent years. Assessing these funds is challenging due to their diverse factor exposures and relatively short history in the Indian market. This paper uses a contemporary return factor model to analyse a systematically selected sample of funds that follow a multifactor investment approach offered by both traditional asset management companies and fintech platforms. Our results reveal significant variation in the alignment of these funds with multifactor investing principles. Contrary to expectations for disciplined and quantitatively orientated funds, most funds show considerable exposure to idiosyncratic risk rather than systematic factors. These findings suggest that many portfolios are designed to maximise alpha through specific asset exposures rather than factor-based returns. Based on these findings, we identify several policy implications for investors, fund managers, and policymakers. The observed variability in the adherence to multifactor principles underscores the need for transparency in strategy design and execution and the adoption of appropriate benchmarks for performance evaluation.

Keywords— Factors, Investment Strategy, Indian Equity, Multifactor Investing, Smart Beta Strategies, Returns-Based Analysis, Portfolio Management

JEL Classification Codes G00, G11, C15

*Director, Invespar Pte Ltd, Email: rajanraju@invespar.com, Phone: +65.62380361

†Professor of Finance and Accounting, Indian Institute of Management, Ahmedabad, Email: joshyjacob@iima.ac.in, Phone: +91.71524878

‡The authors would like to express their sincere gratitude to Mr Anish Teli, Managing Partner at QED Capital, Mumbai, for his valuable comments on an earlier draft of this paper.

1 Introduction

Factor investing, based on the idea that certain characteristics of stocks can predict future returns, has evolved from the application of single factors, such as value, momentum, or low volatility, from the seminal work by Fama and French (1993) to more sophisticated multifactor strategies. These multifactor approaches, which offer exposure to multiple factors in a single investment product, are well established and have recently gained traction in the Indian equity market. This paper examines the performance of multifactor strategies in India, where the unique characteristics of the market and the increasing interest in factor investing present both opportunities and challenges.

In recognition of the expanding universe of factors and their importance in portfolio construction, Morningstar introduced the Factor Profile, which extends beyond their traditional style box. This innovation reflects a broader industry recognition of the critical role that various factors, including size, style, quality, volatility, momentum, liquidity, and yield, play in shaping investment strategies and outcomes. Although multifactor strategies are becoming popular globally, there is still limited research on their performance, especially in emerging markets like India. Limited international evidence shows that multifactor funds often fail to meet their promises and usually perform worse than broad market indices and traditional diversified portfolios in terms of returns and risk-adjusted performance.

In India, the first multifactor mutual fund was launched in 2008. The industry has been slow to grow these offerings, with two funds added in 2019 and 2020. Since last year, two more funds have been launched. Besides the traditional asset management firms, more multifactor strategies are being marketed as Portfolio Management Services (PMS) or Alternative Investment Funds (AIF). The Smallcase platform[1], a relatively new fintech platform, has several multifactor strategies offered by wealth managers.

Despite the increasing presence of multifactor funds in India, there has yet to be a serious attempt to evaluate these strategies. Traditional evaluation metrics, such as fund alpha compared to a benchmark, often fail to fully capture how multifactor portfolios perform and manage risk. These traditional metrics, while widely used, do not show whether the strategy's returns are due to the claimed multifactor premia. The evaluation is further complicated by India's top-heavy equity market, with relatively low liquidity beyond the top 100 firms by market capitalisation, making assessments based on popular benchmark indices less relevant for a multifactor fund. Another significant hurdle in evaluating multifactor strategies, particularly in India, is the lack of a robust sample of strategies. Moreover, the strategies range from well-established ones with long historical data to newer entrants with limited performance history.

These issues underscore the need for an approach that can comprehensively assess multifactor strate-

[1] https://www.smallcase.com/

gies against their stated objectives and the broader market environment. To address this, our study adopts a three-pronged approach. First, we employ a contemporary multifactor model that encapsulates the recent understanding of how stock return characteristics contribute significantly to return variation. Second, we conduct a comparative analysis over a common period across strategies to ensure fairness and direct comparability. Finally, we provide a more in-depth exploration of each strategy's performance and factor exposures over their full available history, presenting these findings separately. This approach not only addresses the issue of comparability, but also enriches the analysis by providing insights into long-term performance under different market regimes.

As mentioned, instead of merely evaluating multifactor strategies against market benchmarks, this study adopts a methodology that examines whether the strategies are true to their multifactor label and what factors are preferred by investment managers in the Indian context. We use a returns-based factor exposure approach (Sharpe, 1992; Raju and Krishnan, 2022) to provide a statistically robust test to evaluate the multi-factor claim. Using the Fama-French five-factor model plus momentum factor to assess whether these strategies truly capture the intended factors. This methodological pivot uncovers what drives performance, instead of just comparing it to a market benchmark.

This research contributes to the multifactor investing dialogue by assessing its practicality within the Indian equity market. It offers a clear methodology for evaluating multifactor strategies, which is useful for investors and wealth managers alike. By addressing the specific drivers of returns, this study provides a detailed assessment of multifactor strategies and offers insight to investors and industry practitioners.

Our analysis indicates a wide variability in the alignment of multifactor strategies with their claimed factor exposures. During the common period between April 2021 and February 2024, no strategy offered by traditional asset management companies (AMCs) or available on the Fintech platform showed statistical evidence of both multifactor exposure and alpha. Only one AMC fund and a recent new fund offering exhibited multifactor exposure without demonstrating alpha.

Extending the analysis to the full historical data available for each strategy, only 10% of the strategies in our sample demonstrated both multifactor exposure and significant positive alpha over a standard factor model. The majority, approximately two-thirds of the strategies, showed no evidence of either multifactor exposure or alpha. These findings underscore the need for rigorous factor-based scrutiny, transparency in strategy design, and the adoption of appropriate benchmarks to accurately evaluate multifactor strategies.

The remainder of this paper is organised as follows: a brief overview of factor investing and a detailed introduction to the multifactor strategies in question, an examination of the empirical evidence surrounding these strategies' performance, and a critical assessment of their efficacy within the Indian equity market landscape.

2 Overview of Stock Return Factors

Factor investing is a strategy that identifies certain asset characteristics, or "factors", that can "predict" cross-sectional stock returns. It has evolved significantly since its inception with the Capital Asset Pricing Model (CAPM) introduced by Sharpe (1964), Treynor (1961), Lintner (1965), and Mossin (1966), establishing the market factor as a primary determinant of stock returns. This foundational concept was expanded by Ross (1976) with Arbitrage Pricing Theory, which posited that multiple factors, beyond just the market factor, influence stock returns.

The emergence of value and size factors, significantly contributed by Basu (1977) and Banz (1981), respectively, marked a critical expansion of factor theory. Value investing, a popular investing approach based on factor models, focusses on stocks that are undervalued relative to their fundamental. Similarly, size investing takes advantage of performance differences between small-cap and large-cap stocks. The integration of these factors into the CAPM framework by Fama and French (1993) through their three-factor model underscored the relevance of value and size in explaining stock returns (known as the Fama-French model). Their innovation of multivariate factors, populated with factors that are largely independent of each other, extended factor theory.

The momentum factor, highlighted by Jegadeesh and Titman (1993), highlights that stocks that have performed well in the recent past tend to continue to perform well into the short term. This led to the expansion of the Fama-French model into a four-factor model by Carhart (1997), incorporating momentum alongside market, size, and value factors.

Later explorations led to the recognition of the explanatory role of investment and profitability factors, as evidenced by the works of Titman, Wei, and Xie (2003) and Novy-Marx (2013). Based on these findings Fama and French (2015) developed an expanded model with five factors. It incorporated investment and profitability along with size, momentum, and market factors, highlighting the evolving nature of factor investing and its ability to explain stock returns more comprehensively. Asness, Frazzini, and Pedersen (2018) expanded on factors linked to q-theory by developing the quality factor.

The volatility factor, identified by Haugen and Heins (1972), and later by Blitz and van Vliet (2007), highlighted how low-volatility stocks tend to outperform their high-volatility counterparts in terms of risk-adjusted returns. This discovery found a strong audience among asset management companies, highlighting the practical implications of factor-based strategies beyond academic circles.

However, the proliferation of identified factors, described as a "factor zoo" (Cochrane, 2011) raised concerns about the validity and relevance of several newly discovered "factors". The heterogeneity in the empirical approach and the data employed by various studies presented a significant challenge in comparing the significance of the explanatory role of various factors. Several different approaches have been proposed to deal with the multiplicity of factors, such as higher significance levels to deal with the issue of multiple testing (Harvey, Liu, and Zhu, 2015), relying on factors backed by theory, and out-of-sample applicability (Mclean and Pontiff, 2016) of the factor returns, are some of the prominent suggestions.

In the Indian context, studies have shown the applicability of various factor findings, suggesting that factor strategies are relevant to the Indian market. Studies such as Agarwalla, Jacob, and Varma (2013, 2017), Raju (2022b,a, 2023a,c), Joshipura and Joshipura (2016), and Jacob, Pradeep, and Varma (2022) show replication of international studies of factors such as size, value, profitability, investment, momentum, low volatility, quality, and more in the Indian equity market. This provides a robust academic basis for the several factor-style products available to investors in India.

3 Factor Models and Practical Considerations

Academic factors are long-short constructions in which a portfolio of stocks with the highest scores of the target factor is bought and a portfolio of stocks with the worst scores of the target factor are sold, leaving the investor with minimal market exposure. Among the alternative factor models used to understand the returns of stocks, such as the Fama-French 3-Factor model (Fama and French, 1993), the 4-Factor models of Carhart (1997), Hou, Xue, and Zhang (2015), and Stambaugh and Yuan (2017), and the Fama-French 5-Factor model (Fama and French, 2015) (FF5). We select FF5 as our benchmark model for its robustness and extensive validation in the academic literature, making it a reliable choice for evaluating multifactor strategies[2].

The FF5 has market, size (SMB), value (HML), operating profitability (RMW), and investment (CMA) as its components. Value captures the return difference between stocks with high and low book-to-market ratios; profitability and investment capture the quality aspect, representing firms with robust profitability and conservative investment policies. To this we add momentum (WML), which measures the tendency of stocks that have performed well in the past to continue performing well in the future.

The FF5 are constructed using six value-weighted portfolios based on size and book-to-market, six based on size and operating profitability, and six based on size and investment. To create the SMB, HML, RMW, and CMA factors, stocks in the universe are divided into two market cap groups and three

[2]See Raju (2022a) for a detailed examination of the model in the Indian context.

respective book-to-market equity (B/M), operating profitability (OP), and investment (INV) groups. *Big* stocks represent the top 90% of the aggregate market capitalisation in September each year, and *small*[3] stocks represent the bottom 10%. The B/M, OP, and INV breakpoints correspond to the 30th and 70th percentiles of respective ratios for the *Big* stocks. The momentum factor, WML, is created using the same method from double-sorts of price and 12-month-skip-1-month momentum. For further details on the factor construction methodology, see Raju (2022b), which adapts the Fama and French approach for India to account for the end of the March fiscal year.

Table 1: A Schematic of Factor Portfolio Construction

Stock Characteristic	Breakpoint (percentile)	Classification	Size		Long-short Factor
			Big	*Small*	
Size	Bottom 90	Small	-	S	
	Top 10	Big	B	-	
Book/market	Bottom 30	Low	BL	SL	
		Neutral	BN	SN	$HML = 1/2(SH + BH) - 1/2(SL + BL)$
	Top 30	High	BH	SH	
Profitability	Bottom 30	Weak	BW	SW	
		Neutral	BN	SN	$RMW = 1/2(SR + BR) - 1/2(SW + BW)$
	Top 30	Robust	BR	SR	
Investment	Bottom 30	Conservative	BC	SC	
		Neutral	BN	SN	$CMA = 1/2(SC + BC) - 1/2(SA + BA)$
	Top 30	Aggressive	BA	SA	
Momentum	Bottom 30	Loser	BL	SL	
		Neutral	BN	SN	$WML = 1/2(SW + BW) - 1/2(SL + BL)$
	Top 30	Winner	BW	SW	

Table 1 outlines the construction of factor portfolios. In FF5, the size factor is defined as:

$$\text{SMB5} = \frac{(SMB_{\text{B/M}} + SMB_{\text{OP}} + SMB_{\text{INV}})}{3}$$

where

$$SMB_{\text{B/M}} = \frac{(SL + SN + SH)}{3} - \frac{(BL + BN + BH)}{3}$$

$$SMM_{\text{OP}} = \frac{(SW + SN + SR)}{3} - \frac{(BW + BN + BR)}{3}$$

and

$$SMB_{\text{INV}} = \frac{(SC + SN + SA)}{3} - \frac{(BC + BN + BA)}{3}$$

By constructing these long-short portfolios, where the ‘long’ position is taken in stocks with high factor scores and the ‘short’ position is taken in stocks with low factor scores, the FF5 model effectively isolates

[3] We use this *big* and *small* nomenclature for the rest of the paper to indicate size. The http://invespar.com/research has size breakpoints in the Invespar factor library. On average, approximately 347 firms from more than 2,900 active firms in the library universe were classified *big* between September 2020 and September 2024.

the individual effects of each factor. All portfolios are well diversified, reducing idiosycratic effects and focussing on systematic effects. This methodology minimises any potential confounding influence between factors, ensuring that the resulting estimate of factors better reflects the target factor. Consequently, this approach improves the power in attributing stock returns to specific factor exposures, providing a clearer understanding of the underlying drivers of performance.

The model aligns well with key investment strategies commonly used by practitioners, such as value investing, quality investing, and momentum trading. Value is represented by HML, quality by RMW and CMA, and momentum by WML. Fama and French (1992) argue that "low BE/ME (a high stock price relative to book value) is typical of firms with high average returns on capital (growth stocks)." Thus, growth is effectively the inverse of value.

Our chosen model ensures that it captures the essential realised characteristics of these strategies and provides a robust framework for evaluating multifactor strategies in the Indian equity market. By integrating these well-established factors, we bridge the gap between academic constructs and practical investment applications, offering a comprehensive tool for strategy evaluation.

Since shorting is very restrictive in the Indian context, practitioners take the long-only leg as a proxy for the value factor. This resultant portfolio is exposed to market risk and has only a portion of the exposure to the drivers of the value factor, similar to driving a car with only two wheels on the road. In this regard, Raju and Krishnan (2022) explore the factor exposures of 16 factor-style Indian indices and conclude that the Indian factor indices capture only part of the full effect of academic factors.

Liquidity is another significant constraint in Indian markets. Therefore, several indices focus their universe in the most liquid area of Indian equity markets, the top 200 stocks by market capitalisation, and others further restrict the universe to those stocks that have futures and options. Raju and Krishnan argue that these choices regarding the universe, weighting, and rebalancing, analogous to selection, allocation, and timing decisions, can create further divergence from theoretical factors, thus providing more options for asset managers and investors to innovate. Furthermore, they demonstrate that multifactor and complex factor indices show that the underlying factor exposures are generally uneven and occasionally non-existent for the claimed factors.

Against this context, multifactor strategies aim to provide investors with rules-based active management, where clearly defined rules make selection and allocation decisions. As these are rule-based, they claim to be not subject to the whims and biases of the investment manager. The rules themselves are claimed to originate in well-accepted academic research and are often enhanced by proprietary models, machine learning, and Artificial Intelligence (AI).

4 Our Sample

As the Indian investment management industry embraces multifactor strategies, selecting a representative sample becomes crucial to understanding these investment approaches. Our selection criteria are designed to cover a wide range of multifactor strategies to avoid sample strategy bias and robustly test our methodology. A primary criterion was that the funds and strategies in our sample had published returns from April 2021 to February 2024.

We start with all the multifactor funds available for retail investors in India offered by Asset Management companies (AMCs) in February 2024. From the 178 equity funds classified as Focussed and Sectoral/Thematic, we identified three funds, with launch dates prior to April 2021, that claimed to use a quantitative model to capture multifactor exposure. These funds claim to employ quality, value, and growth strategies. In addition, we identified one fund launched in July 2023 and a new fund offering for a multifactor ETF. The former had made public the full backtest, and the latter tracks an index whose daily NAVs are public. Consequently, our sample includes these five strategies offered by AMCs.

The level of transparency that funds show at the time of the new fund offering varies significantly. For example, Kotak AMC publicly shares the portfolio construction process and backtested results. Transparency in strategy design, execution, and historical simulated performance allows investors to thoroughly scrutinise the fund's methodology and potential biases.

Next, we looked at strategies available on Smallcase, a fintech platform. These strategies are a basket of securities (like stocks and ETFs) to reflect a particular objective, holding between 2 to 50 securities, offered by SEBI registered professionals. Unlike funds from AMCs, there is a high churn rate of strategies on Smallcases. From the over 1,000 smallcases available on the platform in February 2024, we first selected those live for nearly three years. Second, from this list, we selected strategies classified as factor investing, goal-based, quantamental, quantitative, technical, and thematic by Smallcases. From the several dozen strategies, we finally selected all strategies *explicitly* labelled multifactor in product information.

This results in our sample of 17 strategies, five from traditional AMCs, of which three have historical track records, and 12 strategies on Smallcases. The list of strategies included in the sample and their key characteristics are shown in Panel A and Panel B of Table 2, offered by AMCs and available on Smallcases, respectively.

Table 2: Summary of Multifactor Fund/ETF Strategies

	Name	Short Description	Manager	Number of Holdings	Rebalance	Benchmark	Start Period
		Panel A: Summary of AMC Multifactor Fund/ETF Strategies					
1	Nippon India Quant Fund	Generate capital appreciation by investing in an active portfolio of stocks selected using a Quantitative model.	Nippon India	>30		S&P BSE 200	Apr 2008
2	Tata Quant Fund	Generate medium to long-term capital appreciation by investing in equity and equity-related instruments selected using a quantitative model.	Tata	>30		S&P BSE 200	Jan 2020
3	DSP Quant Fund	Deliver superior returns over the medium to long term through investing in equity and equity-related securities selected using sound investing principles such as growth, value, and quality within risk constraints.	DSP	>30		S&P BSE 200	Jun 2019
4	Kotak Quant Fund	Generate long-term capital appreciation by investing predominantly in equity and equity-related securities selected using a quant model.	Kotak	>30		Nifty 200	Apr 2005
5	Mirae NSC250MomQl ETF	Generate returns commensurate with the performance of the Nifty Smallcap 250 Momentum Quality 100 Total Return Index, subject to tracking error.	Mirae Asset	100	Semi-Ann	Nifty Smallcap 250 Momentum Quality 100	Apr 2005
		Panel B: Summary of Multifactor Strategies on Smallcase					
1	Balanced Multi Factor	Mastering Factor Investing: Diversify, Adapt, and Grow with Wright Balanced.	Wright Research	18	monthly	NIFTY 100	Sep 2019
2	Conservative Multi Factor	Tactical long term out-performance powered by multiple quantitative factors.	Wright Research	15	monthly	NIFTY 100	Dec 2019
3	Flagship Multi Factor	Using the power of Data Science to find undervalued companies which are unlikely to reduce in price	Tolani Investments	40	monthly	NIFTY MIDCAP 150	Apr 2021
4	Growth Multi Factor	Tactical long term out-performance powered by multiple quantitative factors.	Wright Research	17	monthly	NIFTY 100	Dec 2019
5	Gulaq Gear 5	Growth oriented portfolio suited for Moderate to Agressive investors (80% Equity, 20% Debt ETF)	Estee	18	monthly	NIFTY 500	Jun 2020
6	Gulaq Gear 6	Growth oriented concentrated portfolio for Aggressive investors (100% Equity)	Estee	17	monthly	NIFTY 500	Jun 2020
7	MWG Smart Alpha	Identifying Wealth Creators to generate Alpha. Multi-factor Quantitative strategy (Rec Size 5-10L)	My Wealth Guide	24	quarterly	NIFTY 500	Sep 2020
8	Quality - Smart Beta	Established companies that have stood the test of time. Timeless classics.	Windmill Capital	15	annual	NIFTY 100	Aug 2018
9	Quality Smllcap SmartBeta	Quality smallcap stocks with positive momentum trends	Windmill Capital	10	monthly	NIFTY MIDCAP 150	Jan 2021
10	Teji Mandi Flagship	Concentrated portfolio of 15-20 stocks that blends short term tactical bets with long term winners	Teji Mandi	19	As required	NIFTY 500	Sep 2020
11	ViniyogIndia All Weather	Curated portfolio of Low-Risk Stocks & ETFs with strong Risk Management rules	ViniyogIndia	20	quarterly	NIFTY 500	Apr 2021
12	ViniyogIndia Multifactor	Multifactor portfolio where Factor exposure is controlled based on Market Regime forecasts	ViniyogIndia	20	quarterly	NIFTY MIDCAP 150	Apr 2021

Source: Collated from Asset Management websites, Smallcase website and respective fact sheets as on February 2024. The "Start Period" refers to the date of the first monthly return available for each strategy.

For the analysis, we include backtested data[4] and index data, driven by practical considerations and as newer strategies may not yet have accumulated sufficient live performance data. Although inherently less reliable than real-world performance due to potential overfitting and the absence of execution challenges in backtesting, such data nonetheless provide preliminary insights into the strategy's theoretical underpinnings and expected behaviour in various market conditions. The inclusion is of practical interest and relevance to investors evaluating new fund offers.

A recurring theme in the strategies chosen in the sample is the pursuit of long-term performance using a combination of established and innovative quantitative factors and methods. They aim to provide investors with structured rule-based approaches to active management. These approaches promise exposure to well-validated factors such as value, quality, and momentum, enhanced by proprietary models seeking opportunities where academic research-backed quantitative analysis can achieve superior returns.

5 Data Sources

As our sample has strategies from AMCs and Smallcases, index performance from Nifty Indices, and factor returns, we obtain the data from multiple sources as described below.

The net asset values (NAVs) for the sample of funds from AMCs were obtained from LSEG (London Stock Exchange Group) Refinitiv, a global provider of financial market data and infrastructure.

The backtested data for the Kotak Quant Fund was sourced directly from the Kotak AMC website[5]. This source provided data on the fund's performance before it started trading. Live performance data was sourced from LSEG and added to the backtest data.

We accessed the NAVs of the Smallcase strategies directly from the platform's website. The monthly data provided do not include costs, so the actual investor returns are likely to be lower.

The data of Nifty 100, Nifty 200, Nifty 500, and Nifty Smallcap 250 Momentum Quality 100 Total Return Index was retrieved from the Nifty Indices website[6]. The actual performance of the Mirae Asset Nifty Smallcap 250 Momentum Quality 100 ETF will include tracking errors and costs, so the returns investors see may be different. Risk-free rates and additional factor data were obtained from the Invespar Data Library[7]. This comprehensive repository provided risk-free rates for our analysis and the Fama-French and momentum factors specific to the Indian market.

[4] Performance data created through simulations, often excluding operational costs.

[5] Kotak Quant Fund Portfolio Construction Process And Value https://www.kotakmf.com/Information/forms-and-downloads

[6] https://niftyindices.com/reports/historical-data

[7] Available at https://invespar.com/research

All data is on the monthly frequency. The choice of data sources was determined by access and reliability. LSEG and Nifty Indices are well-regarded sources. The Smallcase return calculation methodology uses index values based on hypothetical investments as of the closing prices on rebalance days to measure performance. This process includes adjustments for rebalances and stocks hitting upper/lower circuits, using daily closing prices for calculations. However, it does not account for transaction fees or other costs, likely leading to differences between reported and actual returns. Finally, the Invespar Data Library provides factor returns using the Fama-French methodology, adapted for the end of the March fiscal year in India.

Data availability varies significantly between the different strategies, which presents unique challenges and considerations in our analysis. The Kotak Quant Fund's backtested data and Mirae Asset Nifty Smallcap 250 Momentum Quality Total Return Index data extend back to April 2005, providing a long historical perspective that is particularly valuable for understanding the potential of these strategies over various market cycles. However, these are not realised returns and exclude real-world costs and slippage.

Nippon India Quant Fund offers live data from its inception in April 2008, the longest in our sample. Tata Quant Fund presents the shortest time series among the AMC offerings, with data starting January 2020. Among Smallcase strategies, Windmill Capital's Quality Smart Beta has data from August 2018, making it the oldest strategy in this category.

The availability of data for differing lengths makes our analysis more complex. To address these, we implement a two-pronged approach. First, we carry out a comparative Analysis for Common Period (April 2021 - February 2024): We perform an initial analysis across all strategies with complete data in this common period, ensuring direct comparability and fairness in our evaluation and minimising sample bias.

Second, we carry out an in-depth Full Period analysis: We look deeper into each strategy's performance and factor exposures over their entire available data history, presented separately, to inform the understanding of longer-term performance.

Despite the limitations posed by data variability, our methodology is designed with rigour and transparency. We take into account the varying data lengths and the unique challenges they present. Our aim is to contribute practical insight into the multifactor experience in India, enhancing both academic discussions and improving the evaluation considerations for practitioners.

6 Methodology: Returns-Based Analysis

This study employs a quantitative approach to evaluate the fidelity and efficacy of multifactor strategies, focussing on their alignment with the claimed factor exposures and overall investment performance. Central to our analysis is a returns-based methodology as opposed to a holdings-based analysis. Return-based analysis evaluates the performance of strategies through their historical returns rather than the specific assets held within the portfolio. As the analysis only requires a price series, implementation is easier than a holdings-based analysis. Analysing the returns captures the implicit risk exposures and the strategy's ability to achieve its stated objectives, offering insights that are complementary to those derived from a holding-based approach. Importantly, the returns-based approach reveals realised exposure of the drivers of returns, allowing a comparison of the claimed drivers, making this ideal for our study.

Grounded in the principles of Modern Portfolio Theory (MPT), returns-based analysis posits that the risk and return characteristics of a portfolio, not merely its composition, are paramount in achieving optimal investment outcomes. According to MPT, it is the collective performance of the portfolio's components, as reflected in historical returns, that determines its overall risk profile and efficiency. At the heart of our analysis lies the factor regression model, designed to quantify the degree to which the selected multifactor strategies exhibit exposure to the five factors identified by Fama and French (2015), and the momentum factor.

Specifically, we regress the excess returns of each strategy against the factors of market risk premium (MF), size (SMB), value (HML), profitability (RMW), investment (CMA), and momentum (WML) to obtain factor coefficients. These coefficients reveal the sensitivity of the strategy's returns to each factor, similar to market beta. Each of the coefficients explains to what extent the returns of a strategy are explained by the returns on the factor, providing a direct measure of the exposure of the factor. Raju (2022a) demonstrates that the five-factor model is relevant and effective as an asset pricing model for Indian equities.

Specifically, the factor regression model is formulated as follows:

$$\begin{aligned} R_{i,t} - r_{f,t} = \alpha_i &+ \beta_{mkt,i} MF_t + \beta_{SMB} SMB_t \\ &+ \beta_{HML,i} HML_t + \beta_{RMW,i} RMW_t \\ &+ \beta_{CMA,i} CMA_t + \beta_{WML,i} WML_t + \epsilon_{i,t} \end{aligned} \tag{1}$$

where $R_{i,t}$ is the return of strategy i at time t, $r_{f,t}$ is the risk-free rate at time t, and $\epsilon_{i,t}$ represents the error term. We expect the returns of a well-defined and executed multi-factor strategy to be significantly explained by more than one factor included in the model.

To determine the robustness and reliability of factor exposures, we focus on the statistical significance of the regression coefficients, primarily at the 5% significance level. However, we also evaluate them against a higher threshold of 1% significance level. Such an analysis allows us to critically assess whether each strategy is "true to label," effectively embodying the factor exposures it claims to target.

To address the short-selling constraints in exploiting the short leg of factors in India, as an additional step, we follow Blitz (2012), who proposes an alternative factor model that considers only the long legs of long-short factors. In the analysis described below, we estimate factor models separately for the large-cap and small-cap universe of firms. This alternative construction by Blitz significantly changes the explanatory "factors" and is described by:

$$
\begin{aligned}
R_{it} - r_{f,t} = \alpha + h_i(BV_t - r_{f,t}) + r_i(BR_t - r_{f,t}) \\
+ c_i(BC_t - r_{f,t}) + w_i(WB_t - r_{f,t}) + \epsilon_{it}
\end{aligned}
\tag{2}
$$

where $R_{i,t}$ is the return for strategy i for month t, $r_{f,t}$ is the risk-free rate, $BV_t - r_{f,t}$ the excess return of the *Big Value* portfolio for month t, $BR_t - r_{f,t}$ is the excess return of the *Big Robust* portfolio for month t, $BC_t - r_{f,t}$ is the excess return of the *Big Conservative* portfolio for month t, and $WB_t - r_{f,t}$ is the excess return of the *Winner Big* portfolio for month t. h, r, c, and w are the respective coefficients. The *big* portfolio is a proxy for the large-cap segment representing the most liquid part of the market. It represents the top 10% of the firms by market capitalisation. Limiting the analysis to the large-cap universe better suits the analysis of multifactor strategies that concentrate on the large firms due to liquidity concerns discussed in Section 3[8]. We subtract the returns of these portfolios by the risk-free rate as these are not market-neutral portfolios, unlike their long-short counterparts. Also, note that the size factor is no longer relevant in the estimations and is dropped.

As these are long-only portfolios, all RHS variables are exposed to the market factor, which automatically results in a high correlation with the market factor. This issue is known as multicollinearity for a model that includes the market factor in the RHS. High multicollinearity indicates that independent variables are highly correlated, which can cause instability in coefficient estimates and large standard errors. However, it does not inherently cause the model to explain more variability in the dependent variable and therefore does not lead to a higher adjusted R^2. In the Indian context, with large-cap firms having a disproportional weightage to the market factor, the multicollinearity issue is accentuated.

We verified this by examining the variance inflation factor (VIF), a measure of multicollinearity

[8] These portfolios are part of the 2x3 bivariate sorts that are used to calculate the Fama-French factors (Raju (2022b) describes the methodology in more detail).

with and without the market factor. To set the baseline, the long-short factor model does not show multicollinearity, with VIFs under 5. However, in the *big* long-only model, for the Common Period, with the market factor included, the VIF for the market factor is in excess of 40, and excluding the market factor, the VIF for BV, BR, BC, and WB are between 5 and 7.5, implying that multicollinearity will not distort the regression result for the specification as set out in Equation 2.

One of the concerns in evaluating multifactor strategies with only the universe of large firms is that some of the strategies may focus on the small-cap universe. For example, Raju (2023b) finds that the strategies in Smallcases have significant exposure to *small* firms. Therefore, we employ an alternative model that replaces the *big* size portfolios described in Equation 2 with long-only factor portfolios representing *small* firms (SV, SR, SC, and WS). *small* represents the bottom 90% of Indian firms by market capitalisation. Here, we observe high multicollinearity in the four long-only *small* portfolios. We present the results with this significant caveat.

We adopt a two-pronged approach to effectively employ the available limited data of the funds for the analysis. Initially, we conducted a comparative analysis across all strategies for a common period from April 2021 to February 2024 (common period analysis). This ensures direct comparability and fairness when evaluating strategies against each other within the same market regime.

Subsequently, we dive deeper into each strategy's performance and factor exposures over their entire available historical data range (Full Period analysis). This aspect of our methodology enables a more nuanced understanding of how each strategy has navigated different market conditions over time. This dual approach allows balanced insights, combining direct comparability with an appreciation of long-term strategy performance under diverse market dynamics.

7 Findings and discussion

7.1 *Return performance of funds*

Table 3 presents the summary statistics based on the monthly returns for all strategies and the three benchmarks of the Nifty market for the common period April 2021 to February 2024. The comparison includes average returns (columns 1 and 2), dispersion (columns 3-5), best and worst months (columns 6 and 7), drawdown metrics (columns 8 - 11), and rolling 1 year metrics (columns 12-15). These metrics contextualise our factor regression analysis within the broader landscape of strategy performance, offering a holistic view of the behaviour of each strategy.

Table 3: Summary Statistics of Multifactor Strategies: Common Period (April 2021-February 2024)

Type	Name	CAGR (%) (1)	Geo Mean (% ann) (2)	Stats: Ann Vol (%) (3)	Skew (Mthly) (4)	Kurtosis (Mthly) (5)	Month: Best (%) (6)	Month: Worst (%) (7)	Drawdown: Avg (%) (8)	Drawdown: Avg Days (9)	Drawdown: Longest Days (10)	Max DD (%) (11)	Rolling 1 Year: Mean (% ann) (12)	Rolling 1 Year: Median (% ann) (13)	Rolling 1 Year: Max (% ann) (14)	Rolling 1 Year: Min (% ann) (15)
AMC Fund/ETF	Nippon India Quant Fund	15.82	16.27	13.34	0.12	-0.57	10.02	-4.55	-4.51	51	121	-10.57	15.46	13.89	44.64	-0.49
	Tata Quant Fund	7.82	8.04	11.78	-0.09	-0.71	7.22	-5.22	-7.02	193	547	-14.86	8.97	4.79	27.79	-12.43
	DSP Quant Fund	7.60	7.81	13.84	0.38	0.05	11.38	-6.82	-7.82	233	608	-18.37	4.69	3.08	24.31	-7.87
	Kotak Quant Fund	19.42	19.99	15.57	-0.19	-0.33	11.71	-7.54	-7.41	99	274	-17.79	14.79	10.31	57.46	-1.81
	Mirae NSC250MomQl ETF	21.32	21.95	18.66	-0.34	-0.89	11.16	-9.01	-5.24	98	455	-17.75	17.56	9.80	67.24	-6.65
Smallcases	Balanced Multi Factor	24.84	25.58	17.41	-0.41	-0.47	11.94	-8.24	-9.07	143	244	-10.72	21.64	17.62	79.50	-3.96
	Conservative Multi Factor	9.10	9.36	9.89	-0.47	-0.05	6.72	-5.59	-4.05	183	548	-11.75	7.06	4.18	27.29	-5.97
	Flagship Multi Factor	35.69	36.81	23.94	0.19	-0.48	18.88	-8.64	-5.47	32	123	-13.56	30.94	23.00	84.09	0.25
	Growth Multi Factor	17.87	18.39	17.20	-0.65	-0.26	9.88	-8.99	-18.83	578	578	-18.83	12.30	6.39	63.48	-10.58
	Gulaq Gear 5	25.71	26.48	15.00	-1.20	1.53	9.78	-9.10	-7.28	46	90	-10.51	29.65	23.26	72.59	5.21
	Gulaq Gear 6	33.33	34.37	18.98	-1.16	1.29	12.06	-11.52	-9.22	46	90	-12.54	37.73	29.96	93.06	9.08
	MWG Smart Alpha	14.28	14.69	15.34	-1.08	1.42	9.05	-9.89	-7.14	123	427	-16.80	14.82	6.94	55.65	-12.03
	Quality - Smart Beta	12.58	12.94	16.65	-1.04	1.88	8.94	-12.26	-8.86	194	550	-21.78	6.42	2.80	41.99	-15.05
	Quality Smllcap SmartBeta	28.65	29.52	25.21	0.10	3.52	26.58	-16.65	-8.70	164	458	-20.30	24.12	18.82	78.05	-12.22
	Teji Mandi Flagship	29.21	30.10	20.09	-1.10	1.26	10.69	-13.48	-11.76	230	427	-18.54	27.00	18.05	94.21	-0.77
	ViniyogIndia All Weather	20.00	20.59	16.37	-0.98	2.20	11.92	-12.34	-9.75	245	458	-16.66	15.28	14.14	48.13	-8.21
	ViniyogIndia Multifactor	25.46	26.22	19.50	-0.40	0.32	14.97	-10.21	-7.17	174	458	-12.87	20.28	9.50	84.34	-7.52
Index	NIFTY 100	11.65	11.98	13.46	0.28	-0.72	9.41	-4.86	-6.61	115	244	-10.12	9.92	7.56	33.26	-1.58
	NIFTY 200	12.75	13.11	13.50	0.19	-0.74	9.79	-5.06	-5.48	80	244	-10.45	11.27	9.43	37.02	-1.09
	NIFTY 500	13.51	13.90	13.35	0.09	-0.77	9.73	-5.05	-5.20	80	244	-10.54	12.02	9.87	39.71	-1.22

CAGR is the compounded annual growth rate, GM is the geometric mean, and volatility is the annualized volatility. All these figures are in percentages. The columns under 'Month' give the return in the best month, the worst month, and the average monthly return. The column under 'Rolling 1 year' gives the mean, median, annualized maximum drawdown, and minimum return. Source: NAV of the fund from LSEG Refinitiv; Kotak Quant Fund Backtest from the Kotak AMC website https://www.kotakmf.com/Information/forms-and-downloads; Nifty Smallcap 250 Momentum Quality TR from the Nifty Indices website https://niftyindices.com/reports/historical-data; NAV of the strategies on Smallcase from the platform's website. The statistics are calculated using monthly total returns series.

Between the two categories of funds, those offered by the AMCs and the fintech platform, the strategies on Smallcase generally achieve higher compound annual growth rates (CAGR) (average 23. 1%) than the AMC funds and outperform the NIFTY indexes (between 11.7% and 13.5%). In particular, Flagship Multi Factor (35.7%) Balanced Multi Factor (24.8%) and Gulaq Gear 6 (33.3%) demonstrate significant CAGRs for the period April 2021 to February 2024. In contrast, the AMC sponsored funds, Tata and DSP Quant funds (7.8% and 7.6% respectively) have underperformed the Nifty Indices.

Risk, measured as the annualised standard deviation, shows a wide range: not all multifactor strategies have low volatility. Strategies, like the Mirae Asset Nifty Smallcap 250 Momentum Ql 100 ETF, expectedly show higher volatility (18.7), reflecting their small cap momentum orientation. Conversely, Conservative Multi Factor maintains lower volatility (9.9), consistent with a risk-averse strategy. However, the three funds with higher returns and, more generally, the strategies on Smallcases had higher risk than the market indices. The mean annualised standard deviation for our sample of strategies on Smallcases was 17.9 against the average index value of 13.4.

The skewness of the returns in the Common Period are negative for strategies on Smallcases in our sample (-0.7) and AMCs (-0.02), while the indices are positively skewed (0.2). This negative skewness implies that the strategies on Smallcases and AMCs are more prone to extreme negative returns, indicating a higher risk of significant losses compared to market indices.

The resilience of strategies against market downturns is assessed through drawdown metrics, including average and maximum drawdowns. These metrics (columns 8-11) suggest that some Smallcase strategies exhibit resilience to drawdowns, with faster recovery periods and shallower drawdowns compared to AMC funds/ETFs. However, as a group, the average maximum drawdown (15.4%) and the average drawdown days (180) were worse than the average for the indices (10.4% and 92, respectively). Among the AMC funds, Nippon Quant performed significantly better than the other two funds.

The performance dimensions of the multifactor strategies during the common period show the potential of the strategies to exceed traditional market benchmarks. They also emphasise the importance of considering trade-offs between returns, risk, and market resilience in these investment approaches. The wide variation in outcomes advocates the need for investor due diligence to ensure understanding of expected risks and returns.

Table 4 shows the summary metrics for the Full Period for each strategy. As strategies have different observation periods (column 1), it is inappropriate to draw relative conclusions between strategies.

To set the stage, the full-period average annualised geometric returns for the three indices were better the common period by 173 basis points with a higher annualised volatility (average 22.4 versus 13.4).

Table 4: Summary Statistics of Multifactor Strategies: Full Period (April 2005 - February 2024)

		Period			Stats			Month			Drawdown			Rolling 1 Year			
			CAGR (%)	Geo Mean (% ann)	Ann Vol (%)	Skew (Mthly)	Kurtosis (Mthly)	Best (%)	Worst (%)	Avg (%)	Avg Days	Longest Days	Max DD (%)	Mean (% ann)	Median (% ann)	Max (% ann)	Min (% ann)
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Type	Name																
AMC Fund/ETF	Nippon India Quant Fund	Apr 2008-Feb 2024	8.13	11.13	19.16	-0.07	3.84	25.95	-22.36	-7.75	146	974	-40.02	14.96	10.96	79.55	-25.24
	Tata Quant Fund	Jan 2020-Feb 2024	4.93	5.86	19.16	-1.53	7.75	15.11	-23.97	-13.05	251	547	-31.13	14.41	14.28	41.51	-12.43
	DSP Quant Fund	Jul 2019-Feb 2024	10.40	11.57	18.08	-0.81	4.25	13.01	-20.02	-6.69	111	608	-22.82	17.57	12.95	65.42	-7.87
	Kotak Quant Fund	May 2005-Feb 2024	15.04	20.97	20.16	-0.76	2.93	20.30	-24.76	-8.73	131	760	-50.42	22.37	18.96	93.12	-45.77
	Mirae NSC250MomQl ETF	May 2005-Feb 2024	16.12	22.51	28.07	-0.41	3.54	40.14	-30.77	-12.95	191	1,035	-70.28	27.76	18.60	153.55	-66.51
Smallcases	Balanced Multi Factor	Sep 2019-Feb 2024	23.87	25.66	16.99	-0.39	-0.20	11.94	-9.31	-6.70	88	244	-12.10	38.18	37.54	100.76	-3.96
	Conservative Multi Factor	Dec 2019-Feb 2024	11.47	11.54	10.63	-0.10	-0.11	7.46	-5.59	-3.32	97	548	-11.75	16.83	16.21	45.15	-5.97
	Flagship Multi Factor	Apr 2021-Feb 2024	35.69	36.81	23.94	0.19	-0.48	18.88	-8.64	-5.47	32	123	-13.56	30.94	23.00	84.09	0.25
	Growth Multi Factor	Dec 2019-Feb 2024	18.75	18.87	18.50	-0.97	1.41	11.76	-15.50	-18.66	396	578	-18.83	33.23	27.78	101.17	-10.58
	Gulaq Gear 5	Jun 2020-Feb 2024	29.54	31.65	15.03	-0.75	1.65	13.46	-9.10	-5.88	37	90	-10.51	34.33	35.64	72.59	5.21
	Gulaq Gear 6	Jun 2020-Feb 2024	40.75	43.80	20.22	-0.38	1.60	20.26	-11.52	-7.60	37	90	-12.54	47.85	44.29	101.88	9.08
	MWG Smart Alpha	Sep 2020-Feb 2024	19.03	18.82	15.55	-0.85	1.37	10.37	-9.89	-5.77	99	427	-16.80	16.68	11.55	55.65	-12.03
	Quality - Smart Beta	Aug 2018-Feb 2024	9.98	11.44	17.61	-1.11	3.44	12.18	-18.67	-8.51	134	550	-21.78	12.72	11.35	45.11	-15.19
	Quality Smllcap SmartBeta	Jan 2021-Feb 2024	25.96	29.35	24.44	0.20	3.76	26.58	-16.65	-7.15	131	458	-20.30	29.28	34.93	83.28	-12.22
	Teji Mandi Flagship	Sep 2020-Feb 2024	30.70	30.34	19.00	-1.15	1.54	10.69	-13.48	-8.79	163	427	-18.54	33.91	34.66	94.21	-0.77
Smallcases	ViniyogIndia All Weather	Apr 2021-Feb 2024	20.00	20.59	16.37	-0.98	2.20	11.92	-12.34	-9.75	245	458	-16.66	15.28	14.14	48.13	-8.21
	ViniyogIndia Multifactor	Apr 2021-Feb 2024	25.46	26.22	19.50	-0.40	0.32	14.97	-10.21	-7.17	174	458	-12.87	20.28	9.50	84.34	-7.52
Index	NIFTY 100	May 2005-Feb 2024	10.52	14.56	21.73	-0.37	3.94	29.94	-26.72	-9.21	141	944	-56.95	16.08	13.20	94.55	-53.91
	NIFTY 200	May 2005-Feb 2024	10.72	14.84	22.76	-0.21	4.66	33.93	-27.31	-9.87	197	2,131	-60.02	16.05	12.29	99.02	-56.48
	NIFTY 500	May 2005-Feb 2024	10.68	14.78	22.69	-0.27	4.85	34.48	-27.18	-10.69	219	2,221	-60.44	16.28	12.41	100.73	-56.54

CAGR is the compounded annual growth rate, GM is the geometric mean, and volatility is the annualized volatility. All these figures are in percentages. The columns under 'Month' give the return in the best month, the worst month, and the average monthly return. The column under 'Rolling 1 year' gives the mean, median, annualised maximum drawdown, and minimum return. Source: NAV of the fund from LSEG Refinitiv; Kotak Quant Fund Backtest from the Kotak AMC website https://www.kotakmf.com/Information/forms-and-downloads; Nifty Smallcap 250 Momentum Quality TR from the Nifty Indices website https://niftyindices.com/reports/historical-data; NAV of the strategies on Smallcase from the platform's website. The statistics are calculated using monthly total returns series.

For example, Nippon Quant, the fund with the longest performance record (August 2008 - February 2024), has delivered a significantly lower strategy period geometric return (11.1%) compared to the common period equivalent (16.3%), with a higher annualised volatility (19.2 versus 13.3) - a significantly lower risk-adjusted return. The fund's full period covers part of the Global Financial Crisis, the full Covid period, thereby giving a better estimate of expected returns of the fund across business cycles and market regimes.

In contrast, the DSP Quant fund, with a first observation in July 2019, shows better average returns over its full strategy period, implying that the common period was a relatively challenging time. The Tata Quant fund, starting in January 2020, shows poorer performance in its full period compared to the common period.

The strategies on Smallcases have significantly shorter full strategy period history, so the differences in characteristics should intuitively be smaller than what we see for AMC funds. However, as a group, the strategies were 53 basis points worse in annualised geometric returns, primarily driven by the lower performances of Gulaq Gear 6, Gulaq Gear 5 and MWG Smart Alpha. Only "Quality - Smart Beta" and Quality Smllcap SmartBeta had higher annualised geometric returns. The differences in return characteristics due to a few months of additional data are consistent with the higher annualised standard deviations.

On average, several of the strategies on Smallcases in our sample have outperformed the market indices. Unfortunately, summary statistics do not explain the drivers of returns and do not explain performance. The multivariate factor analysis is intended to examine the dimensions of the returns of the funds and that is where we turn to next.

7.2 Long-Short factor exposures of multifactor strategies

This section discusses the findings of our analysis of multifactor strategies in the Indian equity market using the Common Period and the Full Period. We employ the returns-based approach described in Section 6, explicitly using a regression model to quantify the strategies' sensitivities to the five Fama-French factors (Market Factor (MF), Small Minus Big ($SMB5$), High Minus Low (HML), Robust Minus Weak (RMW), Conservative Minus Aggressive (CMA)) and momentum (Winner Minus Loser (WML)).

The evaluation of a multifactor strategy's effectiveness is centred on its alignment with the target factors, demonstrated by high and statistically significant factor loadings. Such alignment confirms the strategy's ability to capture the intended risk premia, thereby potentially achieving excess returns over the market. We apply the 95% confidence interval to determine the statistical significance of a certain factor in explaining the returns of a strategy. We specifically focus on the coefficients of size, value, quality (profitability and investment), and momentum factors.

Although not essential, a statistically significant alpha, indicating returns beyond those predicted by the factor model, enhances the strategy's merit. However, strategies that lack strong factor alignment do not adhere to the principles of a true-to-label multifactor strategy, even if they exhibit significant alpha. This criterion forms the foundation of our analytical framework, guiding the assessment of each strategy's factor exposures. Note that the benchmarks for such strategies are broad market benchmarks, which is very different from our tests. We argue that because market indices are exposed to the market and size factors, they are poor benchmarks for strategies claiming to outperform due to a proprietary model's multifactor selection, allocation, and timing decisions made by the fund manager.

The adjusted R^2 value of the model serves as an indicator of its explanatory power. A high adjusted R^2 suggests that the factor model effectively explains the strategy's returns, indicating lower idiosyncratic risk. In contrast, low adjusted R^2 values suggest either an inadequately specified model or strategies with high idiosyncratic risk. Given that the factor model used is a standard academic model and the sample strategies reference factors from academic research in their marketing materials, the model should be robust by design. Therefore, low adjusted R^2 values are more likely due to high idiosyncratic risk or the presence of non-equity positions, such as fixed income, gold, commodities, or international equities, within the portfolios. These non-equity positions necessitate extending the factor model to capture the diverse asset classes accurately.

With this approach established, we now turn to the empirical findings of our analysis. Table 5 summarises the exposures of factors for all strategies in the Common Period between April 2021 and February 2024.

In line with our analysis framework, the examination of factor exposures for the benchmark market indices indicates that their returns are well explained by our model, evidenced by a high adjusted R^2 (in excess of 0.95). As expected, these indices exhibit a uniformly positive and significant relationship with the Market Factor (MF). Moreover, as the index universe broadens, the adjusted R^2 increases accordingly, the market beta approaches 1, and the size (SMB) exposure shifts more towards smaller sizes (as indicated by a less negative coefficient).

However, note that the NIFTY 100 accounts for approximately 69% of the free-float market capitalisation of stocks listed on the NSE as of September 29, 2023, compared to the remaining 400 stocks that comprise only 24%, highlighting the top-heavy nature of the Indian equity market[9]. The top-heavy

[9] In contrast, the S&P 500, representing the 500 leading companies in the US, covers around 80% of the available market capitalisation.

Table 5: Factor Exposures of Multifactor Strategies and Market Indicies: Common Period (April 2021-February 2024)

Type	Name	Alpha (1)	MF (2)	SMB5 (3)	HML (4)	RMW (5)	CMA (6)	WML (7)	R-sq Adj. (8)
AMC Fund/ETF	Nippon India Quant Fund	-0.002	0.906***	-0.116**	-0.030	0.152	0.545***	0.079	0.903
		(0.002)	(0.034)	(0.053)	(0.117)	(0.112)	(0.131)	(0.079)	
	Tata Quant Fund	-0.004	0.726***	0.076	0.099	0.103	0.071	-0.205	0.673
		(0.003)	(0.068)	(0.080)	(0.149)	(0.231)	(0.205)	(0.146)	
	DSP Quant Fund	0.000	1.023***	0.087	-0.420***	0.407***	0.284**	-0.233***	0.913
		(0.002)	(0.040)	(0.069)	(0.109)	(0.117)	(0.123)	(0.065)	
	Kotak Quant Fund	-0.000	0.993***	0.213**	-0.076	0.286*	0.295	0.142	0.784
		(0.002)	(0.087)	(0.090)	(0.162)	(0.155)	(0.187)	(0.090)	
	Mirae NSC250MomQl ETF	-0.006**	1.139***	0.753***	-0.317**	0.111	0.606***	0.191*	0.919
		(0.003)	(0.064)	(0.070)	(0.134)	(0.170)	(0.148)	(0.104)	
Smallcases	Balanced Multi Factor	0.007	0.700***	0.571***	0.069	-0.265	-0.341	0.014	0.508
		(0.007)	(0.105)	(0.184)	(0.262)	(0.323)	(0.293)	(0.149)	
	Conservative Multi Factor	-0.002	0.399***	0.326***	0.100	-0.079	-0.123	-0.131	0.464
		(0.004)	(0.062)	(0.097)	(0.166)	(0.228)	(0.203)	(0.093)	
	Flagship Multi Factor	0.004	0.774***	0.886***	-0.023	-0.764	0.547	0.093	0.586
		(0.010)	(0.168)	(0.284)	(0.337)	(0.643)	(0.409)	(0.256)	
	Growth Multi Factor	0.001	0.755***	0.497***	0.171	-0.089	-0.311	-0.087	0.500
		(0.007)	(0.108)	(0.173)	(0.283)	(0.309)	(0.299)	(0.161)	
	Gulaq Gear 5	0.009*	0.632***	0.361**	0.000	-0.027	-0.074	0.193	0.430
		(0.005)	(0.134)	(0.183)	(0.304)	(0.332)	(0.309)	(0.174)	
	Gulaq Gear 6	0.012*	0.775***	0.453**	0.020	-0.029	-0.100	0.267	0.415
		(0.006)	(0.170)	(0.230)	(0.383)	(0.407)	(0.392)	(0.232)	
	MWG Smart Alpha	-0.001	0.639***	0.302	0.285	-0.131	-0.224	-0.175	0.430
		(0.007)	(0.102)	(0.194)	(0.356)	(0.308)	(0.223)	(0.157)	
	Quality - Smart Beta	-0.002	0.794***	0.338*	0.124	0.610	0.231	-0.167	0.357
		(0.007)	(0.154)	(0.199)	(0.321)	(0.416)	(0.325)	(0.168)	
	Quality Smllcap SmartBeta	0.001	0.719***	0.919**	0.479	0.849	-0.069	0.226	0.357
		(0.009)	(0.243)	(0.367)	(0.454)	(0.752)	(0.400)	(0.315)	
	Teji Mandi Flagship	0.012	0.822***	0.742***	-0.098	-0.184	-0.082	-0.143	0.419
		(0.009)	(0.160)	(0.220)	(0.382)	(0.543)	(0.389)	(0.222)	
	ViniyogIndia All Weather	0.006	0.320*	0.760***	0.085	0.076	-0.420	0.129	0.373
		(0.007)	(0.167)	(0.213)	(0.355)	(0.311)	(0.277)	(0.178)	
	ViniyogIndia Multifactor	0.006	0.673***	1.048***	-0.085	-0.109	-0.293	-0.008	0.626
		(0.006)	(0.133)	(0.183)	(0.334)	(0.236)	(0.321)	(0.176)	
Index	NIFTY 100	-0.000	0.933***	-0.217***	0.016	0.133*	0.085	-0.074	0.963
		(0.001)	(0.022)	(0.036)	(0.068)	(0.077)	(0.068)	(0.051)	
	NIFTY 200	0.000	0.959***	-0.150***	-0.012	0.094	0.111*	-0.076*	0.974
		(0.001)	(0.014)	(0.031)	(0.058)	(0.069)	(0.061)	(0.046)	
	NIFTY 500	-0.000	0.966***	-0.060**	-0.049	0.073	0.133**	-0.067	0.978
		(0.001)	(0.012)	(0.028)	(0.048)	(0.064)	(0.057)	(0.044)	

Notes: Standard errors are shown in parentheses below the coefficients. Asterisks denote significance levels: * p<.1, ** p<.05, ***p<.01. Source: NAV of the fund from LSEG Refinitiv; Kotak Quant Fund Backtest from the Kotak AMC website https://www.kotakmf.com/Information/forms-and-downloads; Nifty Smallcap 250 Momentum Quality TR from the Nifty Indices website. https://niftyindices.com/reports/historical-data; NAV of the Smallcase strategy from the smallcase website; Factors from the Data Library: Fama-French Factors, Momentum, and Low-Risk Factors for the Indian Market https://invespar.com/research

market context emphasises the need to understand the possible biases towards larger stocks by funds in India.

During the Common Period, the returns of funds offered by traditional AMCs are generally well explained by our factor model, as evidenced by their high adjusted R^2 (over 0.90). Among these, except for the Tata Quant Fund, we observe statistically significant loadings across multiple factors at the 95% confidence level, underscoring their multifactor strategies. For example, the DSP Quant Fund shows strong exposure to growth (indicated by the negative coefficient for value, HML), quality (exposure to both RMW and CMA), and a significant negative coefficient for momentum (WML. However, the fund does not show statistical alpha to our factor model. In contrast, Nippon shows exposure to quality (CMA) and size, indicating a weaker expression of multifactor exposure.

The index history for the new Mirae Asset ETF shows significant exposure to *small* size and quality (CMA). However, its exposure to momentum is weak, though it shows statistical evidence of exposure to growth. This result places it between the robust multifactor evidence of DSP Quant and the weaker expression by Nippon Quant. The varying exposures highlight the discrepancy between the claims and the actual exposures.

Throughout our Common Period, the Tata Quant Fund fails to exhibit statistical evidence of a consistently executed multifactor strategy, displaying exposure only to the market factor. It has a modest adjusted R^2, indicating that the strategy is not necessarily based on academic factors. The low absolute and relative returns for the fund, as seen in Table 4, also imply that the strategy differs from what is offered by market peers.

Furthermore, the factor exposures observed suggest that the benchmarks typically chosen by the funds (S&P BSE or NIFTY 200) may not be the most appropriate reference points. This insight underscores the complexity of selecting a suitable benchmark for multifactor strategies, highlighting the need for a nuanced approach that considers each fund's specific factor exposures and strategic objectives. Finally, no strategy shows alpha over our factor model.

Unlike funds offered by AMCs, strategies on Smallcases present a different picture in terms of alignment with the factor model. Their adjusted R^2 values generally fall below 0.60, indicating a lower explanatory power of the factor model for these strategies. This suggests a higher degree of idiosyncratic risk, where their characteristics are less attributable to common market factors and more to unique strategy or stock selection criteria.

Several key observations emerge from our analysis, as detailed in Table 5. First, despite this higher idiosyncratic risk, no strategy has shown a statistically significant alpha compared to our factor model. Second, most strategies are exposed to *small* size, with Viniyog India Multifactor having the highest size coefficient. Relative to Mirae Asset's Smallcap ETF, a quarter of the Smallcase strategies show larger size coefficients, implying that these strategies operate in liquidity-constrained areas of the market, which raises questions about their scalability. Third, despite the *small* size exposure, the low market beta suggests either the skill of the fund manager in selection, allocation, and timing decisions or the inefficiencies in the segment of the market with low liquidity. The realised volatility of Viniyog India Multifactor (19.5) relative to the realised volatility of the index tracked by Mirae Asset's ETF (18.7), as shown in Table 3, supports this point.

Finally, there is a lack of evidence of exposure to academic factors, as none of the strategies show any statistically significant coefficients. This absence of significant factor exposures undermines the claims of multifactor exposure for the sample strategies on Smallcases.

In general, the results indicate that the strategies on Smallcases in our sample demonstrate high idiosyncratic risk and significant exposure to *small* size, with no evidence supporting their multifactor exposure claims during the common observation period. We now turn to the Full Period factor exposures. Table 6 summarises the exposures for all the strategies in our sample.

In the Full Period analysis (Table 6), the factor loadings to value and quality for the Nippon India Quant Fund are evident. However, the DSP Quant Fund shows only exposure to quality, indicating a weaker multifactor alignment compared to the Common Period. The Tata Quant Fund continues to lack evidence of multifactor exposures over its longer period.

Both the Kotak Quant Fund and Mirae Asset's ETF show multifactor exposures but also demonstrate alpha. However, based on hypothetical returns, these results provide statistical evidence of the claim to capture multiple factor premia. The true test of their performance will, of course, be seen in the realised results. For practitioners evaluating new offerings, such results would be encouraging.

Amongst the strategies on Smallcases, only the Balanced Multi Factor, Gulaq Gear 5 and Gulaq Gear 6 strategies show evidence of exposure to factors beyond market and size. The first strategy is exposed to quality and the other two to momentum. There is little evidence of strategies for Smallcases that harvest multiple factor premia using our methodology. These strategies continue to show significant exposure to the *small* size factor. Only Gulaq Gear 6 shows a robust alpha for its full strategy period. However, this alpha is not a result of a multifactor strategy. In addition, these strategies maintain a higher idiosyncratic risk and lower adjusted R^2 values, as seen in the Common Period analysis.

Overall, the Full Period analysis reinforces the trends observed in the Common Period, with AMC funds and ETFs showing better alignment with multifactor models compared to strategies on Smallcases. This insight highlights the importance of evidence-based evaluation when considering multifactor strategies in the Indian equity market.

7.3 Long only "factor" exposures of multifactor strategies

Having examined the long-short factor regression results, we now focus on the long-only regression analysis, which includes two alternatives: long-only *big* and long-only *small* portfolios. Table 7 presents these results side by side to compare strategies and indices between the Common Period (April 2021 to

Table 6: Factor Exposures of Multifactor Strategies: Full Period (April 2005 - February 2024)

Type	Name	Period (1)	Alpha (2)	MF (3)	SMB5 (4)	HML (5)	RMW (6)	CMA (7)	WML (8)	R-sq Adj. (9)
AMC Fund/ETF	Nippon India Quant Fund	Apr 2008-Feb 2024	-0.000	0.908***	-0.187***	0.102**	0.206***	0.112*	-0.002	0.927
			(0.001)	(0.030)	(0.043)	(0.045)	(0.074)	(0.058)	(0.033)	
	Tata Quant Fund	Jan 2020-Feb 2024	-0.010***	0.797***	0.109*	0.100	0.071	-0.002	-0.117	0.824
			(0.004)	(0.077)	(0.059)	(0.177)	(0.185)	(0.201)	(0.086)	
	DSP Quant Fund	Jul 2019-Feb 2024	0.000	0.930***	-0.076	-0.147	0.306***	-0.062	-0.079	0.875
			(0.002)	(0.061)	(0.080)	(0.129)	(0.106)	(0.097)	(0.059)	
	Kotak Quant Fund	May 2005-Feb 2024	0.002**	0.955***	0.071*	-0.095**	0.072	0.181***	0.242***	0.905
			(0.001)	(0.027)	(0.036)	(0.047)	(0.073)	(0.064)	(0.026)	
	Mirae NSC250MomQl ETF	May 2005-Feb 2024	0.003**	1.064***	0.741***	0.083	0.148**	-0.064	0.109***	0.939
			(0.001)	(0.038)	(0.046)	(0.075)	(0.071)	(0.079)	(0.035)	
Smallcases	ARQ Prime by Angel One	Aug 2021-Feb 2024	0.002	0.837***	0.818***	-0.245	0.455	0.407	-0.166	0.401
			(0.007)	(0.177)	(0.279)	(0.295)	(0.320)	(0.314)	(0.171)	
	Balanced Multi Factor	Sep 2019-Feb 2024	0.009	0.596***	0.481***	-0.257	-0.454**	0.365**	0.106	0.539
			(0.006)	(0.095)	(0.143)	(0.194)	(0.229)	(0.159)	(0.074)	
	Conservative Multi Factor	Dec 2019-Feb 2024	0.003	0.320***	0.195**	-0.078	-0.205	0.151	-0.024	0.413
			(0.005)	(0.071)	(0.092)	(0.160)	(0.213)	(0.137)	(0.064)	
	Flagship Multi Factor	Apr 2021-Feb 2024	0.004	0.774***	0.886***	-0.023	-0.764	0.547	0.093	0.586
			(0.010)	(0.168)	(0.284)	(0.337)	(0.643)	(0.409)	(0.256)	
	Growth Multi Factor	Dec 2019-Feb 2024	0.003	0.723***	0.462***	-0.308	-0.397	0.357*	0.081	0.594
			(0.006)	(0.091)	(0.141)	(0.222)	(0.252)	(0.189)	(0.090)	
	Gulaq Gear 5	Jun 2020-Feb 2024	0.010**	0.606***	0.481***	-0.157	0.082	-0.086	0.319***	0.430
			(0.005)	(0.096)	(0.155)	(0.231)	(0.241)	(0.227)	(0.114)	
	Gulaq Gear 6	Jun 2020-Feb 2024	0.016***	0.767***	0.664***	-0.169	0.172	-0.222	0.396**	0.406
			(0.006)	(0.122)	(0.204)	(0.300)	(0.304)	(0.338)	(0.174)	
	MWG Smart Alpha	Sep 2020-Feb 2024	0.001	0.669***	0.408**	-0.047	0.083	-0.002	0.092	0.367
			(0.006)	(0.100)	(0.193)	(0.330)	(0.247)	(0.273)	(0.110)	
	Quality - Smart Beta	Aug 2018-Feb 2024	-0.003	0.765***	0.146	-0.028	0.142	0.319*	0.226*	0.498
			(0.004)	(0.092)	(0.122)	(0.181)	(0.277)	(0.188)	(0.117)	
	Quality Smllcap SmartBeta	Jan 2021-Feb 2024	-0.002	0.673***	0.919**	0.326	0.828	0.161	0.366	0.343
			(0.009)	(0.233)	(0.366)	(0.407)	(0.673)	(0.402)	(0.318)	
	Teji Mandi Flagship	Sep 2020-Feb 2024	0.010	0.704***	0.694***	-0.242	-0.304	0.150	0.058	0.388
			(0.009)	(0.137)	(0.224)	(0.343)	(0.466)	(0.295)	(0.143)	
	Value Momentum SC	Jul 2021-Feb 2024	-0.009	0.445***	0.293	0.728**	0.257	-0.308	0.028	0.353
			(0.007)	(0.132)	(0.209)	(0.298)	(0.414)	(0.263)	(0.212)	
	ViniyogIndia All Weather	Apr 2021-Feb 2024	0.006	0.320*	0.760***	0.085	0.076	-0.420	0.129	0.373
			(0.007)	(0.167)	(0.213)	(0.355)	(0.311)	(0.277)	(0.178)	
	ViniyogIndia Multifactor	Apr 2021-Feb 2024	0.006	0.673***	1.048***	-0.085	-0.109	-0.293	-0.008	0.626
			(0.006)	(0.133)	(0.183)	(0.334)	(0.236)	(0.321)	(0.176)	
Index	NIFTY 100	May 2005-Feb 2024	0.000	1.003***	-0.224***	0.018	0.106***	0.014	-0.015	0.984
			(0.001)	(0.012)	(0.016)	(0.027)	(0.037)	(0.030)	(0.014)	
	NIFTY 200	May 2005-Feb 2024	0.000	1.037***	-0.145***	-0.016	0.048	0.016	-0.019	0.979
			(0.001)	(0.018)	(0.013)	(0.032)	(0.034)	(0.031)	(0.013)	
	NIFTY 500	May 2005-Feb 2024	0.000	1.024***	-0.063***	-0.006	0.043	0.016	-0.021*	0.987
			(0.001)	(0.013)	(0.013)	(0.025)	(0.030)	(0.027)	(0.012)	

Notes: Standard errors are shown in parentheses below the coefficients. Asterisks denote significance levels: * p<.1, ** p<.05, ***p<.01. Source: NAV of the fund from LSEG Refinitiv; Kotak Quant Fund Backtest from the Kotak AMC website https://www.kotakmf.com/Information/forms-and-downloads; Nifty Smallcap 250 Momentum Quality TR from the Nifty Indices website. https://niftyindices.com/reports/historical-data; NAV of the Smallcase strategy from the smallcase website; Factors from the Data Library: Fama-French Factors, Momentum, and Low-Risk Factors for the Indian Market https://invespar.com/research

February 2024). Specifically, it details the alpha and loadings of the portfolios *big value* (BV), *robust* (BR), *conservative* (BC), and *winner* (WB)[10] the *small* counterparts SV, SR, SC, and WS, along with the adjusted R^2 values for each regression model.

As expected, the exposure of the indices (NIFTY 100, NIFTY 200, and NIFTY 500) to the RHS

[10]The portfolio names follow academic convention, in which momentum portfolios are classified as Winner and Loser with the size sort following.

variables, and the adjusted R^2 differ significantly between the long-only *big* and *small* models. In the long-only *big* model, the indices demonstrate high adjusted R^2 (over 0.90). In contrast, the *small* model shows low adjusted R^2 values (between 0.3 and 0.4), reflecting the top-heavy nature of the Indian equities market. The three market indices show exposure to quality (BR and BC), not to value or momentum, and do not show any alpha in our model. The regression results against the *small* model indicate that the model is a poor choice for the indices, highlighting the differences in explanatory power between the *big* and *small* models while simultaneously demonstrating the insight of analysing the differences in the two models.

Table 7: Long Only Factor Exposures of Multifactor Strategies: Common Period (April 2021 - February 2024)

Type	Name	Long-only *big* portfolios: Alpha (1)	BV-r_f (2)	BR-r_f (3)	BC-r_f (4)	WB-r_f (5)	R-sq Adj. (6)	Long-only *small* portfolios: Alpha (7)	SV-r_f (8)	SR-r_f (9)	SC-r_f (10)	WS-r_f (11)	R-sq Adj. (12)
AMC Fund/ETF	Nippon India Quant Fund	-0.001	0.128	0.222**	0.476***	0.023	0.839	0.004	-0.355	0.201	0.871*	-0.236	0.363
		(0.002)	(0.114)	(0.104)	(0.111)	(0.117)		(0.006)	(0.578)	(0.481)	(0.511)	(0.384)	
	Tata Quant Fund	-0.007**	0.076	0.126	0.420**	0.034	0.608	-0.005	0.427	-0.280	0.717	-0.529**	0.466
		(0.003)	(0.150)	(0.207)	(0.197)	(0.148)		(0.004)	(0.370)	(0.294)	(0.516)	(0.254)	
	DSP Quant Fund	-0.007***	-0.293***	0.581***	0.651***	-0.056	0.870	-0.003	-0.096	0.455	0.260	-0.188	0.210
		(0.002)	(0.113)	(0.115)	(0.131)	(0.100)		(0.008)	(0.729)	(0.580)	(0.747)	(0.334)	
	Kotak Quant Fund	0.000	-0.118	-0.101	0.709***	0.414***	0.766	0.005	-0.367	0.689	0.541	-0.171	0.543
		(0.004)	(0.141)	(0.144)	(0.153)	(0.160)		(0.006)	(0.441)	(0.456)	(0.407)	(0.343)	
	Mirae NSC250MomQl ETF	-0.002	-0.238	-0.573*	1.301***	0.522***	0.711	-0.007**	-0.027	-0.055	0.299	0.628**	0.854
		(0.005)	(0.158)	(0.308)	(0.294)	(0.173)		(0.003)	(0.302)	(0.265)	(0.364)	(0.270)	
Smallcases	Balanced Multi Factor	0.010	0.441*	-0.283	-0.013	0.420**	0.347	0.012**	-1.476**	1.128**	1.370**	-0.138	0.598
		(0.007)	(0.251)	(0.191)	(0.244)	(0.194)		(0.006)	(0.729)	(0.574)	(0.618)	(0.383)	
	Conservative Multi Factor	-0.001	0.283*	-0.183	0.121	0.105	0.303	-0.001	-0.365	0.306	0.731*	-0.254	0.494
		(0.004)	(0.151)	(0.127)	(0.151)	(0.121)		(0.004)	(0.389)	(0.316)	(0.403)	(0.225)	
	Flagship Multi Factor	0.015*	0.762**	-0.903***	0.428	0.351	0.321	0.010	0.071	0.042	1.034	-0.245	0.516
		(0.009)	(0.329)	(0.262)	(0.402)	(0.228)		(0.008)	(1.144)	(0.678)	(1.379)	(0.459)	
	Growth Multi Factor	0.003	0.448	-0.162	0.022	0.320	0.374	0.005	-1.198**	1.030*	1.340**	-0.329	0.573
		(0.007)	(0.286)	(0.223)	(0.260)	(0.199)		(0.006)	(0.584)	(0.552)	(0.569)	(0.435)	
	Gulaq Gear 5	0.014**	0.259	0.147	-0.144	0.291	0.339	0.012**	-1.201**	0.133	1.759***	-0.065	0.501
		(0.007)	(0.230)	(0.229)	(0.270)	(0.200)		(0.006)	(0.473)	(0.383)	(0.609)	(0.348)	
	Gulaq Gear 6	0.020**	0.351	0.191	-0.259	0.388	0.327	0.017**	-1.624***	0.264	2.268***	-0.104	0.495
		(0.008)	(0.311)	(0.279)	(0.346)	(0.269)		(0.007)	(0.602)	(0.470)	(0.776)	(0.438)	
	MWG Smart Alpha	0.000	0.532	-0.030	0.072	0.003	0.349	0.004	-0.619	0.692	1.083	-0.514	0.442
		(0.006)	(0.345)	(0.223)	(0.323)	(0.219)		(0.006)	(0.673)	(0.494)	(0.687)	(0.413)	
	Quality - Smart Beta	0.000	0.498*	0.551**	-0.073	-0.265	0.360	0.003	-1.141	0.878	1.118	-0.193	0.312
		(0.006)	(0.297)	(0.227)	(0.296)	(0.256)		(0.009)	(0.759)	(0.616)	(0.786)	(0.366)	
	Quality Smllcap SmartBeta	0.013	0.366	-0.391	0.241	0.426	0.125	0.008	-0.384	1.529**	-1.094	0.949**	0.444
		(0.011)	(0.531)	(0.301)	(0.562)	(0.311)		(0.008)	(1.163)	(0.746)	(1.566)	(0.413)	
	Teji Mandi Flagship	0.014	0.464	-0.162	0.157	0.194	0.232	0.013	-0.907	0.794	1.039	-0.074	0.451
		(0.009)	(0.353)	(0.310)	(0.387)	(0.280)		(0.009)	(1.012)	(0.703)	(0.955)	(0.513)	
	ViniyogIndia All Weather	0.013	0.349	-0.204	-0.318	0.381	0.069	0.010	-1.299**	1.263***	0.479	0.293	0.431
		(0.008)	(0.384)	(0.240)	(0.434)	(0.252)		(0.006)	(0.586)	(0.384)	(0.772)	(0.363)	
	ViniyogIndia Multifactor	0.011	0.123	-0.505*	0.309	0.575**	0.180	0.003	0.036	0.450	-0.093	0.408	0.571
		(0.009)	(0.348)	(0.296)	(0.378)	(0.271)		(0.006)	(0.873)	(0.645)	(0.964)	(0.565)	
Index	NIFTY 100	-0.003	0.165*	0.581***	0.169*	-0.043	0.897	0.003	-0.327	0.377	0.910	-0.507	0.276
		(0.002)	(0.091)	(0.106)	(0.096)	(0.077)		(0.008)	(0.730)	(0.567)	(0.658)	(0.338)	
	NIFTY 200	-0.003*	0.147*	0.504***	0.250***	-0.011	0.924	0.002	-0.256	0.291	0.912	-0.472	0.345
		(0.002)	(0.078)	(0.089)	(0.082)	(0.064)		(0.008)	(0.686)	(0.539)	(0.620)	(0.328)	
	NIFTY 500	-0.003*	0.121*	0.422***	0.318***	0.028	0.939	0.001	-0.210	0.235	0.861	-0.385	0.423
		(0.002)	(0.064)	(0.071)	(0.070)	(0.059)		(0.007)	(0.639)	(0.500)	(0.572)	(0.304)	

Notes: Standard errors are shown in parentheses below the coefficients. Asterisks denote significance levels: * p<.1, ** p<.05, ***p<.01. Source: NAV of the fund from LSEG Refinitiv; Kotak Quant Fund Backtest from the Kotak AMC website https://www.kotakmf.com/Information/forms-and-downloads; Nifty Smallcap 250 Momentum Quality TR from the Nifty Indices website. https://niftyindices.com/reports/historical-data; NAV of the Smallcase strategy from the smallcase website; Factor portfolio returns from the Data Library: Fama-French Factors, Momentum, and Low-Risk Factors for the Indian Market https://invespar.com/research. The $BV - r_f$, $BR - r_f$, $BC - r_f$, and $WB - r_f$ are the excess returns over risk-free for *big value*, *robust*, *conservative*, and *winner* portfolios. The equivalent for long-only *small* portfolios are $SV - r_f$, $SR - r_f$, $SC - r_f$, and $WS - r_f$.

Analysis of the regression of long only *big* versus long only *small* for the strategies reveals significant differences in explanatory power. Generally, long-only *big* portfolios show higher adjusted R^2 values than their *small* counterparts, suggesting more robust explanatory power for large-cap "factors". For example, the DSP Quant Fund exhibits an adjusted R^2 of 0.9 in the *big* model, contrasting sharply with 0.2 in the *small* model. Similarly, the Tata Quant Fund and the Kotak Quant Fund show higher adjusted R^2 values in the *big* model compared to the *small* model. This disparity reiterates the large-cap tilts for these funds seen in Table 5.

As expected, Mirae Asset's Nifty Smallcap 250 multifactor ETF demonstrates better explanatory power with an adjusted R^2 of 0.85 in the long-only *small* model, compared to 0.71 in the *big* model. Both perform worse than the long-short factor model, which has an adjusted R^2 of 0.92.

For the strategies on Smallcases, the long-only *big* model generally shows lower adjusted R^2 values (average 0.28) than the *small* model (average 0.49), indicating higher exposures to small caps. For instance, the Balanced Multi Factor strategy has an adjusted R^2 of 0.35 in the *big* model, improving to 0.60 in the *small* model. The average adjusted R^2 of the long-short factor model for Smallcases strategies is 0.46, slightly lower than that of the long-only model.

As expected, a higher adjusted R^2 in the long-only *small* model and significant $SMB5$ exposure in the long-short regression are related. Strategies with notable small-cap exposure in the long-short model tend to have higher adjusted R^2 values in the long-only *small* model, reflecting the influence of small-cap factors.

To determine multifactor exposure in AMC funds, we look for the presence of two or more significant coefficients at the 95% significance level. The preferred model between *big* and *small* is chosen based on the higher adjusted R^2. For example, the Nippon India Quant Fund is more aligned with the long-only *big* model with an adjusted R^2 of 0.84[11], showing significant coefficients for quality (BR) and investment (BC). This result is consistent with the long-short model, which also shows significant quality (CMA) exposure.

In Section 7.2, the DSP Quant Fund showed multifactor exposure to value (HML), quality (RMW and CMA), and momentum (WML). The preferred long-only *big* model confirms this with significant coefficients for value (BV) and quality (BR and BC). Conversely, the preferred model for the Kotak Quant Fund, the long-only model *big*, shows significant coefficients for quality (BC) and momentum (WB), whereas the long-short model does not show exposure to multifactors. Mirae Asset's Nifty Smallcap 250 multifactor ETF prefers the long-only *small* model, with significant momentum (WS) exposure. Despite the higher adjusted R^2 in the *small* model, multicollinearity issues lead us to favour the results of the *big* model, similar to the findings of the long-short factor model.

[11] The *small* model has a lower adjusted R^2 of 0.36

For Smallcase strategies, in the Common Period, the *small* model is the preferred choice with its higher adjusted R^2, but the inherent multicollinearity makes the reliability of coefficients an issue. With this caveat, 50% strategies in our sample show statistically significant multifactor exposures. Growth and quality are the most preferred, and one strategy has exposure to quality and momentum. Using the *big* long-only model, only the Flagship Multifactor shows statistically significant multifactor exposure. None of the strategies showed multifactor exposure using the long-short factor model in the Common Period (Table 5).

Finally, after examining the alpha coefficients, no AMC strategies showed a positive alpha. Among Smallcases strategies, Gulaq Gear 5 and Gulaq Gear 6 exhibit positive and statistically significant alphas in both *big* and *small* long-only models. In addition, Balanced Multi Factor demonstrates alpha in the *small* long-pnly model. Recall that only two strategies showed evidence of alpha, albeit with a weaker significance (at 10%) in the long-short model.

The lack of evidence of multifactor exposure or alphas using the long-only models strenghthens the evidence that the claims of multifactor exposures are not being delivered. Although long-only models offer some additional insight, the *small* version poses significant interpretation challenges due to the high multicollinearity. The clearer design and construction of the long-short model offer more robust results, with market effects being better isolated from factor effects. Their use to explain and understand returns bypasses the operational constraints of short sales. The factor model gives an estimate of the underlying expected returns of a market-neutral factor, which is very useful in the limited scope of decomposing strategy returns.

The other point that emerges is the choice of the benchmark for multifactor strategies. The decomposition of market benchmarks based on market capitalisation does not show multifactor exposure, making these indices poor benchmarks for multifactor strategies. Although alpha to broad market benchmarks by several strategies is evident in Tables 3 and 4, the strategies do not show alpha in a standard academic factor model. This calls into question the claims of superior returns for these strategies when using more appropriate multifactor benchmarks.

The equivalent results of the long-only model over the Full Period are shown in Table A2. The findings are similar to those from the Common Period analysis.

7.4 A Practical Classification Schema

To determine whether the funds in our sample are true-to-label multifactor funds, we propose to classify them based on two criteria: factor exposure and alpha over the factor model. In our view, the first criterion is central to being labelled as a multifactor fund, and the second is a desirable criterion. According to the criteria, for a fund to be classified as a multifactor fund, it must show significant exposure to at least two of the following factors: value (HML), quality (either CMA or RMW), and momentum (WML). As these are long-only strategies, exposure to the market factor (MF) is expected, and size (SMB) is ignored at this initial level.

The identification of the factor loading of funds is the same as described in Section 6 of the paper. As our regression analysis provides a test of significance of the factor exposure, we suggest that the coefficients should be significant at 95% equivalent to a t-statistic of approximately 2.0 or above.[12]. Consequently, the classification matrix is summarised in Table 8.

Table 8: Classification of Multifactor Funds Based on Alpha and Factor Exposures

		Factor Exposure	
		Significant	**Inconsistent or Not Significant**
Alpha	**Positive & Significant**	True-to-Label	Alpha Not Multifactor
	Not Significant or Negative	No Alpha Multifactor	No Alpha Not Multifactor

Applying the above classification matrix to the results provided in Table 5, we obtain the labelling of the funds as given in Table 9. There is no true-to-label multifactor strategy that has a statistically significant alpha in the period. There are only two strategies that meet our criteria for any two significant coefficients of value, quality, or momentum. None of the strategies on the fintech platform show multifactor characteristics according to our criteria. The low adjusted R^2 highlights the high idiosyncratic risk due to the small number of holdings in their portfolios.

Table 9: Classification of Sample Multifactor Strategies: Common Period (April 2021 - February 2024)

		Factor Exposure		**Total**
		Significant	**Inconsistent or Not Significant**	
Alpha	**Positive & Significant**			
	Not Significant or Negative	2	15	17
Total		2	15	17

An analogous classification for the Full Period is provided in Table A1 in the Appendix. The merit of the returns-based approach adopted here is the minimal data requirements (monthly strategy prices and

[12] A more strict criterion could follow Harvey et al. (2015) who suggests a t-statistic of 3.0.

factor returns) and the focus on evaluating claims of outperformance and multifactor exposure using a well-understood statistical test.

7.5 Discussion of the results

Within our sample, funds offered by AMCs, with their broader, more consistent factor loadings and higher explanatory power, align more closely with the multifactor investing thesis. In contrast, strategies on Smallcases exhibit a diverse range of factor exposures, often with lower adjusted R^2 values, hinting at a more idiosyncratic risk profile.

In essence, the factor exposure analysis of Smallcase strategies underscores the diversity and complexity inherent in aligning with multifactor investing principles. During the Common Period, no Smallcase strategy has evidence realised multifactor exposures, and in the Full Period, only one strategy fulfils our 95% confidence criteria for multifactor exposure. The strategies demonstrate a focus on *small* size, in both the long-short and long-only models. Finally, they show high idiosyncratic risk (lower adjusted R^2 values. Our findings show that selecting a concentrated portfolio of firms with high target characteristics does not lead to exposure to the premia associated with the characteristics. The high cointegration of the *small* value, quality, and momentum portfolios, resulting in high multicollinearity, implies that creating multifactor portfolios in the universe of firms with *small* size is challenging.

The Nifty 250 Momentum Quality 100 index shows that multifactor exposure can be obtained in this segment. Smallcase strategies with higher idiosyncratic risks imply fund manager decisions are likely driven by primarily return outcomes rather than a systematic attempt at harvesting multiple factor premia. In a quantitative sense, these strategies are likely overfitted or rely on fund manager discretion, which is the opposite of systematic factor design.

The divergence in factor exposures between AMC funds and Smallcase strategies highlights the importance of a thorough factor-based analysis when considering these investment strategies, especially for investors seeking to minimise stock-specific risk while capturing factor premia. Not all multifactor strategies are alike and true-to-label. This analysis not only underscores the complexities inherent in the implementation of multifactor strategies but also highlights the critical role of portfolio construction and diversification in achieving true-to-label multifactor investments.

A related issue is the choice of benchmarks. Our findings show that market indices are primarily exposed to market and size factors as designed. Consequently, they serve as poor benchmarks for multifactor strategies. This is evident in the significant outperformance of the strategies on Smallcaes over the Nifty market indices, while not showing the same level of alpha versus the long-short or long-only factor models.

In late 2017, SEBI introduced the regulation to categorise and rationalise mutual fund schemes to clarify the attributes of mutual fund schemes and bring about uniformity in the functioning of AMCs. In this spirt, benchmarks for multifactor strategies should reflect the size universe of the strateggy, and the target factors the fund manager claims exposure to. In addition, our findings show the dynamic nature of exposures over time. Any good benchmark should show significant and consitent exposure to the target factors.

8 Implications of the findings

Our analysis has revealed several key insights into the performance, factor exposures, and the varying degree of alignment with multifactor investment principles of strategies in our sample. This section outlines some key practical implications derived from our findings, underscoring the relevance of rigorous factor-based scrutiny of multifactor strategies.

Firstly, **investors** seeking enhanced returns through factor investing face the challenge of identifying true-to-label multifactor strategies in the context of a variety of marketed options. Our analysis highlights the importance of examining factor exposures and idiosyncratic risks beyond just summary statistics. Investors should use returns-based analysis to verify a strategy's alignment with its stated factor mandates, gaining a comprehensive understanding of the underlying drivers of returns. This approach helps inform decision making, enabling investors to choose strategies that genuinely embody the multifactor philosophy and are positioned to capture the intended factor premia. In addition, it helps to differentiate between absolute performance and the drivers behind these returns. As our analysis shows, the Smallcase strategies in our sample, despite outperforming traditional market benchmarks, may not truly show with multifactor exposure or alpha over academic multifactor models.

Secondly, the findings highlight the need for **portfolio managers** to maintain transparency in factor exposures and the systematic design of their strategies. Portfolio construction should accurately reflect the claimed factor exposures while minimising the idiosyncratic risk that could detract from factor-based returns. Our findings indicate that concentrated portfolios are unlikely to demonstrate multifactor exposure due to higher idiosyncratic risk. Using a universe of firms of *small* size makes extracting multiple factor premia challenging. Managers of small-cap scchemes must take extra care to ensure that they are harvesting the premia they claim. Furthermore, our analysis suggests potential overfitting or reliance on discretionary decision making in strategies, emphasising the need for a disciplined rule-based approach in strategy design. As factors are empirical, portfolio managers should maintain transparency in communicating their multifactor strategy. The level of transparency demonstrated by Kotak Quant Fund serves as an excellent role model, providing a clear description of how the portfolio is constructed and managed, and sharing backtest results over several years. This allows investors to conduct thorough due diligence using both holdings-based and returns-based approaches.

Factor portfolios are, by design, well-diversified. In the Indian context, Raju and Agarwalla (2021) argue that portfolios of 15-20 stocks are not sufficiently diversified. To reduce diversifiable risk by 90% with 90% confidence, a portfolio of 40-50 stocks is required. A careful selection and allocation decision could reduce the number of stocks or increase confidence levels. Short-selling constraints in India make it more challenging to harvest pure factor premia. Raju and Krishnan (2022) showed that long-only factor-style indices had varying exposure to the claimed factor premia. Managers should carefully disentangle the beta of the market from the target factor premia when constructing long-only portfolios. Furthermore, as we have shown, isolating factor premia in small-cap stocks is particularly difficult. The observations of the study can help managers in portfolio construction and management. Portfolios should be robustly evaluated for true-to-label factor exposure.

Portfolio managers must also consider the appropriateness of benchmarks, ensuring that they align with the strategy's factor exposures to accurately reflect performance relative to multifactor objectives. Both size and target factors influence the choice of the benchmark. Most factor-style indices encompass large or large- and midcap universes, with semiannual rebalancing and factor-tilt weight schemes. Managers may have very different allocation and timing decisions, making these factor-style indices inappropriate. The use of an independent academic factor model alongside a factor-style index might serve as a more appropriate benchmark. Publishing factor exposures in the factsheets using academic long-short or long-only asset pricing models would be another way to ensure clear reporting of the realised factor exposures.

Thirdly, the findings call for **policymakers** to enhance regulatory oversight and guidelines to ensure the integrity and transparency of these strategies. Policymakers should advocate for standardised disclosure of factor exposures and the methodologies underlying strategy construction, helping investors in the due diligence process. The establishment of benchmarks for the evaluation of multifactor strategies could further support the ecosystem, providing a framework for comparing and evaluating claims according to the label. In addition, regulators could consider mandating periodic audits of factor-based strategies to ensure compliance with disclosed methodologies and to verify the accuracy of reported factor exposures. Encouraging educational initiatives to improve investor understanding of multifactor investing principles would also be beneficial.

Finally, the nuanced dynamics of multifactor investment, as shown in our analysis, has broader implications for the Indian equity market. The adoption of multifactor strategies, with an emphasis on systematic rule-based investment processes, could contribute to market efficiency and the maturation of the investment landscape. However, the varying degrees of adherence to multifactor principles call for a cautious approach, underscoring the value of continuous research and education in this domain. Furthermore, the growth of transparent and well-designed multifactor strategies could attract a wider range of investors, enhancing liquidity and depth in the market. Encouraging collaboration between academia and industry can also lead to the development of more robust multifactor models tailored to the unique characteristics of the Indian market.

9 Conclusion

The paper investigates the performance and factor exposures of strategies that claim to be multifactor in the Indian equity market. Using twin criteria (a) evidence of multifactor exposure and (b) a positive alpha (outperformance) over a standard factor model, we find no statistical evidence of funds fitting the multifactor label during a common period selected for all the 17 strategies (from April 2021 and February 2024).

One of the funds offered by a traditional AMC showed multifactor exposure, but without alpha. One recent new fund offering similarly showed multifactor exposure, but did not demonstrate alpha. All the 12 strategies available on the fintech platform showed significant idiosyncratic risk without statistical evidence of the factors claimed during the Common Period.

When the criteria were applied to the full history of each of the 17 strategies in the sample, two strategies demonstrated both multifactor exposure and positive significant alpha. Two other strategies showed multifactor exposure without evidence of alpha, while two more funds exhibited alpha without multifactor exposure. The remaining strategies, about two-thirds of the sample, showed no evidence of either multifactor exposure or alpha. This variability among multifactor funds underscores the critical need for transparency in the design and execution of these strategies, as well as the adoption of appropriate benchmarks for performance evaluation.

The strategies on Smallcases generally outperformed the Nifty market indices, their benchmark. However, against the long-short and long-only academic factor models, only two of the smallcases in the sample showed alpha. This raises the question of the appropriateness of the benchmark for multifactor strategies. There is a case for the adoption of appropriate benchmarks for performance evaluation.

Our exploration of multifactor strategies in India is at a moment when the market's appetite for 'smart beta' offerings is growing. Although our analysis attempts to address the inherent issues of an early stage of multifactor investing in India, the sample has certain limitations. First, reliance on historical and backtested data allows sample bias to creep in despite our best efforts. The overfitting bias arising from the use of backtested data is another common source of data bias. Second, our factor model may cover only some relevant risk factors. However, the model is extendable. Adding international equity or fixed income, two potential new dimensions for multifactor strategies, is straightforward. Consequently, while our findings offer a foundational methodology for evaluating multifactor strategies, the results are preliminary and call for a caution in generalising the findings.

The practical implications derived from our research provide actionable insights for investors, portfolio managers, and policymakers, guiding them toward a more evidence-based approach to multifactor investing. For investors, the emphasis on returns-based analysis to verify factor alignment offers a methodical approach to strategy selection. Portfolio managers are reminded of the importance of maintaining transparency and adhering to a systematic rule-based strategy design to ensure true-to-label multifactor strategies. Policymakers are encouraged to enhance regulatory oversight and establish guidelines to support the integrity and transparency of multifactor strategies.

Looking forward, the ever-changing landscape of multifactor investing in the Indian equity market poses both challenges and opportunities for further research. The changing nature of empirical factor exposures, the inclusion of emerging factors, and the influence of market conditions on strategy performance necessitate ongoing exploration. Subsequent studies could examine the long-term performance of multifactor strategies and their ability to withstand various market cycles.

References

Agarwalla, Sobhesh K.; Jacob, Joshy, and Varma, Jayanth R. Four factor model in Indian Equities Market. *IIM, Ahmedabad Working Papers*, WP No 2013 09 05, 2013. URL http://www.iimahd.ernet.in/~jrvarma/Indian-Fama-French-Momentum/four-factors-India-90s-onwards-IIM-WP-Version.pdf.

Agarwalla, Sobhesh K.; Jacob, Joshy, and Varma, Jayanth R. Size, Value, and Momentum in Indian Equities. *Vikalpa*, 42(4):211–219, 2017. doi: 10.1177/0256090917733848. URL https://doi.org/10.1177/0256090917733848.

Asness, Clifford S.; Frazzini, Andrea, and Pedersen, Lasse Heje. Quality Minus Junk. *Review of Accounting Studies*, 24(1):34–112, May 2018. doi: 10.1007/s11142-018-9470-2.

Banz, Rolf W. The Relationship Between Return and Market Value of Common Stocks. *Journal of Financial Economics*, 9(1):3–18, 1981.

Basu, Sanjoy. Investment Performance of Common Stocks in Relation to their Price-Earnings Ratios: A Test of the Efficient Market Hypothesis. *The Journal of Finance*, 32(3):663–682, 1977.

Blitz, David. Strategic Allocation to Premiums in the Equity Market. *The Journal of Beta Investment Strategies*, 2(4):42–49, 2012. ISSN 2154-7238. doi: 10.3905/jii.2012.2.4.042. URL https://jii.pm-research.com/content/2/4/42.

Blitz, David C. and van Vliet, Pim. The Volatility Effect. *The Journal of Portfolio Management*, 34(1):102–113, 2007. ISSN 0095-4918. doi: 10.3905/jpm.2007.698039. URL https://jpm.pm-research.com/content/34/1/102.

Carhart, Mark M. On Persistence in Mutual Fund Performance. *The Journal of Finance*, 52(1):57–82, 1997. doi: 10.1111/j.1540-6261.1997.tb03808.x. URL http://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.1997.tb03808.x.

Cochrane, John H. Presidential Address: Discount Rates. *Journal of Finance*, 66(4):1047–1108, August 2011.

Fama, Eugene F and French, Kenneth R. The Cross-Section of Expected Stock Returns. *the Journal of Finance*, 47(2):427–465, 1992.

Fama, Eugene F. and French, Kenneth R. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56, 1993. doi: 10.1016/0304-405x(93)90023-5.

Fama, Eugene F. and French, Kenneth R. A Five-Factor Asset Pricing Model. *Journal of Financial Economics*, 116(1):1–22, 2015. doi: 10.1016/j.jfineco.2014.10. URL https://ideas.repec.org/a/eee/jfinec/v116y2015i1p1-22.html.

Harvey, Campbell R.; Liu, Yan, and Zhu, Heqing. … and the Cross-Section of Expected Returns. *The Review of Financial Studies*, 29(1):5–68, 10 2015. ISSN 0893-9454. doi: 10.1093/rfs/hhv059. URL https://doi.org/10.1093/rfs/hhv059.

Haugen, Robert A and Heins, A James. On the Evidence Supporting the Existence of Risk Premiums in the Capital Market. *SSRN eLibrary*, page 33, December 1972. doi: https://dx.doi.org/10.2139/ssrn.1783797.

Hou, Kewei; Xue, Chen, and Zhang, Lu. Digesting anomalies: An investment approach. *The Review of Financial Studies*, 28(3): 650–705, 2015.

Jacob, Joshy; Pradeep, KP, and Varma, Jayanth Rama. Performance of Quality Factor in Indian Equity Market. *SSRN eLibrary*, page 49, December 2022. doi: https://dx.doi.org/10.2139/ssrn.4284686.

Jegadeesh, Narasimhan and Titman, Sheridan. Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance*, 48(1):65, 1993. doi: 10.2307/2328882.

Joshipura, Mayank and Joshipura, Nehal. The Volatility Effect: Evidence from India. *Applied Finance Letters*, 5, 06 2016. doi: 10.24135/afl.v5i1.32.

Lintner, John. The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. *The Review of Economics and Statistics*, 47(1):13–37, 1965. ISSN 00346535, 15309142. URL http://www.jstor.org/stable/1924119.

Mclean, R. David and Pontiff, Jeffrey. Does Academic Research Destroy Stock Return Predictability? *The Journal of Finance*, 71(1): 5–32, 2016. doi: https://doi.org/10.1111/jofi.12365. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/jofi.12365.

Mossin, Jan. Equilibrium in a Capital Asset Market. *Econometrica*, 34(4):768–783, 1966. ISSN 00129682, 14680262. URL http://www.jstor.org/stable/1910098.

Novy-Marx, Robert. The Other Side of Value: The Gross Profitability Premium. *Journal of Financial Economics*, 108(1):1–28, 2013. doi: 10.1016/j.jfineco.2013.01.003.

Raju, Rajan. A Five-Factor Asset Pricing Model: Preliminary Evidence from India. *Available at SSRN 4190426*, page 33, August

2022a. doi: https://dx.doi.org/10.2139/ssrn.4190426. URL https://ssrn.com/abstract=4190426.

Raju, Rajan. Four and Five-Factor Models in the Indian Equities Market. *SSRN eLibrary*, page 37, March 2022b. doi: http://dx.doi.org/10.2139/ssrn.4054146. URL https://ssrn.com/abstract=4054146.

Raju, Rajan. Low-Risk Anomaly: Evidence from India. *SSRN eLibrary*, page 29, March 2023a. doi: https://dx.doi.org/10.2139/ssrn.4398656. URL https://ssrn.com/abstract=4398656.

Raju, Rajan. smallcases Investment Performance: A Returns-Based Factor Analysis. *SSRN eLibrary*, page 18, February 2023b. doi: http://dx.doi.org/10.2139/ssrn.4344044. URL https://ssrn.com/abstract=4344044.

Raju, Rajan. The 52-Week High Effect and Momentum Investing: Evidence from India. *SSRN eLibrary*, page 26, October 2023c. doi: https://dx.doi.org/10.2139/ssrn.4587697.

Raju, Rajan and Agarwalla, Sobhesh Kumar. Equity Portfolio Diversification: How Many Stocks Are Enough? Evidence from India. IIMA Working Papers WP 2021-02-02, Indian Institute of Management Ahmedabad, Research and Publication Department, February 2021. URL https://ideas.repec.org/p/iim/iimawp/14648.html.

Raju, Rajan and Krishnan, Harish. Factor Indices in India: Factor Exposures and Style Analysis. *Available at SSRN*, page 26, June 2022.

Ross, Stephen. The Arbitrage Pricing Theory. *Journal of Economic Theory*, 13(3):341–360, 1976.

Sharpe, William F. Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk. *The Journal of Finance*, 19 (3):425–442, 1964. doi: https://doi.org/10.1111/j.1540-6261.1964.tb02865.x. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.1964.tb02865.x.

Sharpe, William F. Asset Allocation: Management Style and Performance Measurement. *Journal of portfolio Management*, 18(2): 7–19, 1992.

Stambaugh, Robert F. and Yuan, Yu. Mispricing Factors. *The Review of Financial Studies*, 30(4):1270–1315, 2017. ISSN 08939454, 14657368. URL http://www.jstor.org/stable/26166315.

Titman, Sheridan; Wei, K.C. John, and Xie, Feixue. Capital Investments and Stock Returns. NBER Working Papers 9951, National Bureau of Economic Research, Inc, September 2003. URL https://ideas.repec.org/p/nbr/nberwo/9951.html.

Treynor, Jack L. Market Value, Time, and Risk. *SSRN eLibrary*, page 46, August 1961. doi: https://dx.doi.org/10.2139/ssrn.2600356.

A Supplementary Material

Table A1: Classification of Sample Multifactor Strategies: Full Period (April 2005 - February 2024)

		Factor Exposure		**Total**
		Significant	**Inconsistent or Not Significant**	
Alpha	**Positive & Significant**	2	2	4
	Not Significant or Negative	2	11	13
Total		4	13	17

Table A2: Long Only Factor Exposures of Multifactor Strategies: Full Period (April 2005 - February 2024)

,

Type	Name	Period	Long-only *big* portfolios						Long-only *small* portfolios					
			Alpha	BV-r_f	BR-r_f	BC-r_f	WB-r_f	R-sq Adj.	Alpha	SV-r_f	SR-r_f	SC-r_f	WS-r_f	R-sq Adj.
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Type	Name													
	Nippon India Quant Fund	Apr 2008-Feb 2024	-0.000	0.266***	0.490***	0.127*	-0.005	0.902	-0.001	-0.138	0.218*	0.561***	-0.045	0.710
			(0.001)	(0.043)	(0.062)	(0.072)	(0.059)		(0.002)	(0.159)	(0.130)	(0.207)	(0.114)	
	Tata Quant Fund	Jan 2020-Feb 2024	-0.012***	0.339**	0.189	0.333	0.015	0.745	-0.009**	-0.096	0.539*	0.446	-0.316	0.723
			(0.005)	(0.158)	(0.241)	(0.244)	(0.175)		(0.004)	(0.509)	(0.277)	(0.428)	(0.202)	
AMC Fund/ETF	DSP Quant Fund	Jul 2019-Feb 2024	-0.004	0.091	0.799***	0.200	-0.122	0.812	0.000	-0.473	0.622**	0.546	-0.164	0.550
			(0.003)	(0.119)	(0.150)	(0.174)	(0.123)		(0.005)	(0.535)	(0.276)	(0.637)	(0.227)	
	Kotak Quant Fund	May 2005-Feb 2024	0.005***	-0.001	0.245***	0.256***	0.407***	0.887	0.003	-0.244	0.228*	0.236	0.451***	0.746
			(0.001)	(0.040)	(0.065)	(0.068)	(0.051)		(0.002)	(0.160)	(0.137)	(0.223)	(0.109)	
	Mirae NSC250MomQl ETF	May 2005-Feb 2024	0.006**	0.430***	0.508***	0.039	0.142	0.799	0.003*	0.073	0.384***	0.252	0.272***	0.924
			(0.002)	(0.079)	(0.155)	(0.152)	(0.104)		(0.002)	(0.133)	(0.120)	(0.185)	(0.103)	
	Balanced Multi Factor	Sep 2019-Feb 2024	0.013**	0.085	-0.358**	0.453**	0.397***	0.416	0.009*	-0.785*	-0.110	1.458***	-0.001	0.572
			(0.005)	(0.146)	(0.171)	(0.221)	(0.127)		(0.005)	(0.447)	(0.233)	(0.439)	(0.182)	
	Conservative Multi Factor	Dec 2019-Feb 2024	0.003	0.171*	-0.096	0.195	0.056	0.365	0.003	-0.402	0.001	0.850***	-0.155	0.469
			(0.003)	(0.098)	(0.114)	(0.143)	(0.096)		(0.004)	(0.255)	(0.184)	(0.310)	(0.140)	
	Flagship Multi Factor	Apr 2021-Feb 2024	0.015*	0.762**	-0.903***	0.428	0.351	0.321	0.010	0.071	0.042	1.034	-0.245	0.516
			(0.009)	(0.329)	(0.262)	(0.402)	(0.228)		(0.008)	(1.144)	(0.678)	(1.379)	(0.459)	
	Growth Multi Factor	Dec 2019-Feb 2024	0.007	0.146	-0.187	0.345	0.375**	0.494	0.003	-0.778*	-0.076	1.496***	-0.032	0.621
			(0.005)	(0.174)	(0.178)	(0.235)	(0.150)		(0.006)	(0.412)	(0.295)	(0.449)	(0.203)	
	Gulaq Gear 5	Jun 2020-Feb 2024	0.017***	0.006	0.209	-0.202	0.493***	0.317	0.010*	-0.138	-0.045	0.249	0.406	0.324
			(0.007)	(0.157)	(0.230)	(0.289)	(0.172)		(0.006)	(0.566)	(0.277)	(0.727)	(0.334)	
	Gulaq Gear 6	Jun 2020-Feb 2024	0.025***	0.056	0.348	-0.414	0.642***	0.302	0.016**	-0.104	0.071	0.205	0.449	0.293
Smallcases			(0.009)	(0.212)	(0.321)	(0.414)	(0.245)		(0.007)	(0.825)	(0.386)	(1.044)	(0.496)	
	MWG Smart Alpha	Sep 2020-Feb 2024	0.006	0.197	0.242	-0.021	0.175	0.285	0.004	-0.499	0.490	0.603	-0.012	0.370
			(0.006)	(0.259)	(0.272)	(0.381)	(0.169)		(0.005)	(0.532)	(0.424)	(0.645)	(0.407)	
	Quality - Smart Beta	Aug 2018-Feb 2024	0.000	0.093	0.409**	0.094	0.133	0.477	-0.001	-0.738	0.056	0.837	0.379	0.437
			(0.004)	(0.159)	(0.195)	(0.247)	(0.211)		(0.005)	(0.475)	(0.254)	(0.528)	(0.239)	
	Quality Smllcap SmartBeta	Jan 2021-Feb 2024	0.012	-0.081	-0.400	0.446	0.624**	0.086	0.002	0.158	0.930	-1.481	1.216***	0.372
			(0.010)	(0.477)	(0.325)	(0.588)	(0.285)		(0.008)	(1.379)	(0.748)	(1.713)	(0.466)	
	Teji Mandi Flagship	Sep 2020-Feb 2024	0.016*	0.225	-0.200	0.326	0.257	0.216	0.010	-0.272	0.216	0.582	0.154	0.400
			(0.009)	(0.267)	(0.284)	(0.361)	(0.195)		(0.008)	(0.909)	(0.553)	(0.723)	(0.367)	
	ViniyogIndia All Weather	Apr 2021-Feb 2024	0.013	0.349	-0.204	-0.318	0.381	0.069	0.010	-1.299**	1.263***	0.479	0.293	0.431
			(0.008)	(0.384)	(0.240)	(0.434)	(0.252)		(0.006)	(0.586)	(0.384)	(0.772)	(0.363)	
	ViniyogIndia Multifactor	Apr 2021-Feb 2024	0.011	0.123	-0.505*	0.309	0.575**	0.180	0.003	0.036	0.450	-0.093	0.408	0.571
			(0.009)	(0.348)	(0.296)	(0.378)	(0.271)		(0.006)	(0.873)	(0.645)	(0.964)	(0.565)	
	NIFTY 100	May 2005-Feb 2024	-0.000	0.290***	0.610***	0.040	0.034	0.952	-0.000	-0.172	0.389***	0.415	0.057	0.728
			(0.001)	(0.033)	(0.044)	(0.052)	(0.039)		(0.002)	(0.184)	(0.144)	(0.271)	(0.130)	
Index	NIFTY 200	May 2005-Feb 2024	-0.000	0.313***	0.610***	0.058	0.036	0.952	-0.000	-0.169	0.353**	0.522*	0.025	0.760
			(0.001)	(0.035)	(0.046)	(0.048)	(0.042)		(0.002)	(0.183)	(0.142)	(0.276)	(0.139)	
	NIFTY 500	May 2005-Feb 2024	-0.000	0.333***	0.592***	0.070	0.019	0.962	-0.000	-0.123	0.345***	0.495**	0.026	0.802
			(0.001)	(0.034)	(0.045)	(0.049)	(0.043)		(0.002)	(0.165)	(0.131)	(0.246)	(0.130)	

Notes: Standard errors are shown in parentheses below the coefficients. Asterisks denote significance levels: * p<.1, ** p<.05, ***p<.01. Source: NAV of the fund from LSEG Refinitiv; Kotak Quant Fund Backtest from the Kotak AMC website https://www.kotakmf.com/Information/forms-and-downloads; Nifty Smallcap 250 Momentum Quality TR from the Nifty Indices website. https://niftyindices.com/reports/historical-data; NAV of the Smallcase strategy from the smallcase website; Factor portfolio returns from the Data Library: Fama-French Factors, Momentum, and Low-Risk Factors for the Indian Market https://invespar.com/research. The $BV-r_f$, $BR-r_f$, $BC-r_f$, and $WB-r_f$ are the excess returns over risk-free for *big value*, *robust*, *conservative*, and *winner* portfolios. The equivalent for long-only *small* portfolios are $SV-r_f$, $SR-r_f$, $SC-r_f$, and $WS-r_f$.