“Long” Factors, not “Short” change : Long Only Factor Portfolios in India

Rajan Raju* Anish Teli†‡

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ABSTRACT

We show that monthly rebalanced, equal-weighted, long-only winner portfolios, drawn from the top 200 stocks in India, built using systematic rules that underpin popular factors of momentum, low volatility and quality deliver alpha for the period under study. The market exposure is significant across all the style strategies we looked at. Therefore, correlations between the strategies are significantly higher than those observed for academic factor returns. We include alternate calculation methodologies for some factors and find that not all implementations of factor strategies are the same. Not all strategies have high turnover. Indeed, strategies like low volatility and quality show fairly low turnover. Factor exposure persistence over time varies across strategies and persistence should be considered when implementing factor-style strategies. We also find that size and sectoral preferences of factors are dynamic and could reduce perceived diversification benefits. Finally, we show that alpha for momentum, low volatility and quality strategies survives real-world implementation costs. While winner portfolios using momentum, low volatility, and quality rank higher than the broad S&P 200 Index over the period under study, there is not one factor-style that is a consistent winner.

Keywords— Factors, Factor Investing, India
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*Director, Invespar Pte Ltd, Email: rajanraju@invespar.com, Phone: +65.62380361

†Managing Partner and Principal Officer, QED Capital Advisors, Email: anish.teli@qedcap.com, Phone: +91.9819871330
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1 Introduction

Recently there has been considerable excitement around factor investing[1] in India. Domestic asset managers are offering funds tracking these 'strategy indices' to retail investors[2]. Internationally, factor investing has been more established with a longer track record. The field has seen a veritable explosion of academic literature on factor models originating with the work of Fama (1972). There is abundant academic evidence for the existence of various factor premiums in equity markets, such as the value, momentum, low-risk, and quality premiums (Fama and French (1988, 2011, 2012); Jegadeesh and Titman (1993); Asness et al. (2013); Ang et al. (2008); Frazzini and Pedersen (2014); Asness et al. (2018)). The evidence that these factors exist in multiple emerging markets is also considerable (de Groot et al. (2012b); Cakici et al. (2013, 2016); Hanauer and Linhart (2015)). Standard academic factor portfolios, following Fama and French (1988), take hypothetical long positions in stocks with attractive characteristics and simultaneously take hypothetical short positions in stocks with unattractive characteristics. Factor returns are computed from these market-neutral portfolios. While theoretically elegant, this long-short approach is practically not feasible in most markets. Practical expressions of factor investing are not market-neutral long-short portfolios. Rather they are usually long-only portfolios with significant market exposure. Most practical factor-based portfolios are more of a 'factor-tilt' effort than a factor replicating investment with significant divergence in returns between the two.

Factor models are 'empirical asset pricing models' and rely on historical data to show possible out-performance relative to a benchmark. Rational asset pricing models interpret these premia as the compensation to bear systematic risks not captured by the market factor (Fama and French, 1993). Behavioural theories view such premia arising from arbitrage or behavioral biases (De Bondt and Thaler, 1985; Lakonishok et al., 1994; Daniel and Titman, 1997; Barberis et al., 1998). Since the 1980s, factors like size, value, and momentum were shown to deliver returns that could not be explained by capital asset pricing models. Hundreds of 'factors' allegedly offering a unique source of return have emerged since then. With cheap, powerful computing power, increasingly accessible machine learning algorithms, easy-to-code high-level computer languages, associated statistical libraries, and access to data sources, brute force is used to find correlations between millions of variables in the hunt for 'factors'. This has resulted in a large number of false positives[3]. While the more obvious and egregious false positives are easily dealt with, it is very difficult to learn whether a factor has a true economic basis. "There are three kinds of lies: lies, damned lies, and statistics". Unfortunately for factor investing, in its empirical nature lies its Achilles heel.

[1] Also called styles, strategy, smart-beta or alternative beta investing, especially in marketing brochures and the popular financial press.

[2] for example, *UTI Nifty200 Momentum 30 Index Fund* from UTI Mutual Fund tracking the Nifty200 Momentum Index. https://utimf.com/nfo/uti-nifty-200-momentum-30-index-fund/
Kotak Nifty Alpha 50 ETF from Kotak Mutual Fund tracking the Nifty Alpha 50 Index. https://www.kotakmf.com/Products/nfo/etf-funds/Kotak-Nifty-Alpha-50-ETF/Dir-G

[3] Arnott et al. (2018) highlight an example using the first three letters of a firm's ticker symbol. They find a strategy that buys stocks listed on the New York Stock Exchange with the letter 'S' as the third letter and shorts stocks with the letter 'U' as the third letter has spectacular performance backtests and meets all the common statistical tests. However, this is an instance of 'correlation without causation. See Harvey and Liu (2017) for more examples of false 'discoveries'.

Internationally there is a vigorous and heated debate around taming the 'factor zoo'[4] (see Harvey et al. (2015); Mclean and Pontiff (2016); de Prado (2018); Blitz and Hanauer (2020); Bartram et al. (2020); Hou et al. (2018) amongst others). This debate, like the hunt for factors, is empirically based. In India, however, there is little formal research on factor investing. Ansari and Khan (2012); Joshipura and Joshipura (2016); Agarwalla et al. (2017); Raju (2019) are a few examples of research into factors in India. The increasing interest in factor investing requires more detailed India-specific empirical analysis to separate evidence from myth. There are significant implementation issues in India for strategies that short individual stock. So any examination of factor strategies in the Indian context necessarily entails examining the long-only legs. We examine empirical evidence to answer questions such as: Do long-only factor strategies outperform the broader market? How much factor/market exposure do these strategies have? What is the turnover experienced? Do such strategies persist over time? What is their size/sectoral composition? Do they survive in real-world implementations?

We differ from traditional academic studies that examine the contribution of the long and short legs of portfolios from academic long/short factor datasets. Practitioners in India rightly point out that such academic portfolios include a number of small and micro-caps. The theoretical returns consequently shrink significantly in implementation. Unfortunately, there is little research in the performance of long-only factor portfolios that are implementable and where costs of implementation are factored in. This paper addresses this gap. We build decile portfolios from the most liquid and traded universe of stocks in the Indian equity market. The top decile portfolio is our factor-strategy portfolio. This approach makes our findings more aligned to real-world implementations of factor strategies and, therefore, of direct interest to practitioners. We use statistical techniques to examine potential alpha, factor exposure for each implementation, turnover, persistence and correlations, size and sectoral bias and finally whether the alpha survives implementation costs. Wherever possible we use industry definitions so that the results are meaningful for practitioners. The broad and holistic approach provides a unique evidence-based insight on long-only strategies in the Indian context.

Using time-series data from December 2006 for the S&P BSE 200 constituents, we show that some long-only top decile portfolios deliver alpha in India. Factor-tilt strategies have varying exposure to underlying factors. Not all implementations of a factor are equal. In fact, in some implementations, the desired factor exposure is completely absent. Market exposure is significant across all the strategies we looked at, and therefore correlations between the strategies are significantly higher than those indicated in academic research. Turnovers vary significantly between strategies. Not all turnovers are high. Factor exposure persistence varies across strategies and should be an important consideration when choosing strategies. Finally, we show that for some strategies alphas do survive real-world implementation after costs. Our analysis shows that factor strategies are not the panacea or silver bullets for investors. Like any investment, factor strategies have risks such as volatility, potentially long periods of under performance, and changing factor exposure.

This paper is one of the first to empirically explore several possible factor strategies using a consistent

[4]a term coined by Cochrane (2011)

methodology within the Indian context. By building and examining portfolios implementable in the real-world, the paper contributes pragmatic and real-world insight to the growing debate on the attractiveness and viability of factor strategies in India using an evidence based approach. The framework developed could serve as a process to evaluate factor-tilt strategies by various industry participants including regulators, index providers, asset managers, wealth advisers and investors. More importantly, we hope this paper will encourage further research into factor investing within the Indian context and allow a similar empirically-driven robust debate around factor investing in India as ongoing in developed equity markets.

The rest of the paper is organized as follows: Section 2 covers the literature, in Section 3, we discuss our methodology and data; in Section 4, we present our results; and we conclude in Section 5.

2 Literature Review

Amongst the ever-growing factor zoo, we take a conservative approach in our choice of factors to investigate in this study. In the main, we focus on the long-established factors that have been exhaustively tested across markets and periods. There is a wide range of academic research on factors, some of which we have referenced earlier. The size, value, and momentum factors laid out by Fama and French (1993, 2011) and Jegadeesh and Titman (1993) are among the most established factors. In the Indian market, Agarwalla et al. (2013, 2017) show strong evidence of the existence of these factors in their exploration and construction of the Fama-French Four-Factor model. Agarwalla et al. (2014) showed the existence of the 'betting-against-beta' factor in India[5]. Joshipura and Joshipura (2016); Ali et al. (2021) look at the low-volatility premium in India.

Long-only factor strategy returns are not the same as theoretical factor returns (Arnott et al., 2017). While marketing brochures tend to gloss over the technical nuances that differentiate the two implementations, any serious consideration of factor-tilt performance must account for the differences between the academic factors and real-world implementation. Huij et al. (2014) compare long-only and long-short implementations of factors and conclude that "*investors should carefully consider the pros and cons of long-only and long-short approaches when implementing factor investing*". Blitz et al. (2020) found that most of the value-add from long-short factor strategies comes from the long legs. Raju and Chandrasekaran (2019) analysed a large-cap long-only momentum factor-tilt portfolio in India and concluded that such a strategy does show partial exposure to the momentum factor. Raju (2019) looked at the quality factor tilt in India, adapting the work done by Asness et al. (2018), again in the large-cap space.

In addition to size, value, momentum, low-risk, and quality, we include a couple of factor-tilt indices that popular index providers have created (high beta and growth). Factor portfolios can be constructed in many different ways. For example, a value strategy can be based on just the market-to-book ratio or a combination of value parameters such as price-to-earnings or dividend yield. Or a momentum strategy constructed with a look-

[5]Following the approach outlined by Frazzini and Pedersen (2014).

back of 12 months with or without adjusting for volatility. The specific strategy execution method[6] can result in a significant difference to the outcome of the factor portfolio. Israel et al. (2017) argue that "*skillful targeting and capturing of style premia may constitute a form of alpha on its own — one we refer to as 'craftsmanship alpha'*". The construction complexity increases with multi-factor portfolios. One fundamental decision that portfolio managers managing multi-factor portfolios need to deal with is whether combining individual factor portfolios is equivalent to building a bottom-up multi-factor portfolio. Bender and Wang (2016) analyse this question and find that interaction between individual factors impacts portfolio performance significantly. They conclude '*both intuition and empirical evidence favour bottom-up multi-factor portfolio construction*'. For this paper, we focus on single-factor portfolios but look at alternate construction approaches for some of the factors to highlight that portfolios claiming to track the same factor are not necessarily the same in their factor exposure.

We use the CAPM (one-factor) and the multi-factor market models in analysing factors and factor tilts. Internationally, the excellent Ken French Data Library[7] with factor returns updated monthly and going back till 1926 for the US Markets, 1990 for Developed Markets, and 1989 for Emerging Markets serves as a reference dataset for much of the research. Agarwalla et al. (2013), at the Indian Institute of Management, Ahmedabad (IIMA), created and maintain a four-factor Fama-French Data Library for Indian Market[8] with data from 1993 onwards. Recently, the dataset was updated[9] with changes in data sources and refinements in methodology and run till March 2021[10] With the growing interest in factor investing in India, the importance of having an independent factor-return dataset for India that is freely and publicly available cannot be overstated. Such datasets serve as a vital control mechanism to ensure the fair implementation and marketing of factor strategies through enabling transparent and independent research.

3 Methodology and Data

3.1 Methodology

We look at the size, value, momentum, low-risk, quality, growth and beta factors for this study. Our universe is the S&P BSE 200 constituents which we have collated from December 2006 through to October 2021[11]. The total number of firms in the universe is 405[12]. The S&P BSE 200 is rebalanced semi-annually. The constituents are rolled over every month-end between two rebalancing periods

[6]choice of the parameter(s), weights for these parameters, transformations of the underlying parameter, the portfolio formation look-back period, the portfolio rebalancing frequency, the number of instruments in a portfolio, and weighting scheme of portfolio amongst many others.

[7]https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[8]https://faculty.iima.ac.in/~iffm/Indian-Fama-French-Momentum/

[9]We have also run our analysis using the legacy dataset which stopped Dec 2019. We do not present this analysis in the paper. However, our findings and conclusions remain the same indicating the robustness of our approach.

[10]The dataset uses CMIE's Prowess DX https://prowessdx.cmie.com/ which provides three data releases every year in March, September and December. The authors plan to have three releases every year.

[11]The index consists of the top 200 companies by float-adjusted market-cap listed on the BSE Ltd. It is widely used as a benchmarking tool and covers more than 85% of the market cap of all the companies listed on the BSE Ltd. https://www.spglobal.com/spdji/en/idsenhancedfactsheet/file.pdf?calcFrequency=M&force_download=true&hostIdentifier=48190c8c-42c4-46af-8d1a-0cd5db894797&indexId=1852729

[12]inclusive of all firms that were part of the index at any point during our observation period.

The choice of the top 200 stocks by free-float market capitalization minimises the inclusion of liquidity-constrained stocks in the analysis. Without adequate liquidity in the stocks, any factor strategy will face serious implementation issues which erode theoretical returns[13]. de Groot et al. (2012a) attribute the high transaction costs incurred in many factor strategies implemented in the US stock market to excessive trading in small caps. Our choice of S&P BSE200 minimises this effect thereby significantly reducing the possible trading costs. Impact costs, arising from thin liquidity is a second factor that contributes to shrinkage of returns between theory and practice. Getting data on impact costs for illiquid instruments is almost impossible. Like Schrödinger's cat, one can either measure liquidity or the cost, but not both across a range of liquidity simultaneously. By choice of universe, we avoid the hidden, but real, costs of the lack of liquidity which shrink theoretical returns very quickly in the real world and estimate with some confidence the potential reduction between the theoretical and real-world returns. As most real-world strategies will use some optimisation techniques to reduce excessive turnover and impact costs, our estimates for the unoptimised strategies are likely on the higher end of realised costs. *Our estimates of shrinkage, consequently, are conservative, but reasonable.*

From the S&P BSE 200 constituents, we create equally-weighted decile portfolios for each factor monthly. Each decile has 20 stocks. We do not follow the standard academic process of creating double-sorted portfolios on Size and Value. This is done for two pragmatic reasons: a. the current factor-tilt indices do not follow the double-sort methodology and, b. among wealth advisers and DIY investors minimising administrative procedures is preferred. On any month, from the 200 firms, adopting the double sorting approach potentially will leave some of the double-sorted portfolios with too few firms. Our approach follows real-world implementation.

The weighting scheme of a portfolio is an important driver of performance (see Bender and Wang (2015)). The capitalisation-weighted (CW) "market" portfolio has a central role in asset pricing Sharpe (1966) especially in the real-world investable portfolios. Most indices, and therefore index-tracking funds/ETFs, are CW. Academic research has used equal-weighted (EW) portfolios as a norm. Plyakha et al. (2014) show "*with monthly rebalancing, an equal-weighted portfolio outperforms a value-weighted portfolio in terms of total mean return, four-factor alpha, and Sharpe ratio*". Some index providers offer "signal-weighted-capitalisation-scaled" (SWCT) portfolios. Here the weights are determined by the strength of the signal and then scaled appropriately by the capitalisation of the firm. Academic research on SWCT portfolios is limited. We adopt the EW approach in our analysis for two reasons: first, it is aligned to general academic research methodology, and second, it remains an easily understood, intuitive method[14].

Under a market-neutral factor model, the top decile stocks would be the "longs" and the bottom decile, the "shorts". In our analysis, the top decile is the "winner" portfolio and the bottom decile, the "loser". For portfolios in general and winner portfolios in particular, we compute various performance metrics divided into

[13] see Arnott et al. (2017) for a detailed overview on how factor returns shrink in the real world

[14] One area of future research is to examine other weighting schemes for factor-tilt strategies.

two groups. First, the core performance measures. We compute returns for each decile on a close-to-close basis using month-end returns. To measure the risk-return trade-off we use the raw Sharpe ratio. The raw Sharpe ratio is measured as the mean return divided by the volatility. The raw Sharpe provides a starting baseline to compare the performance of portfolios in general. For all deciles, we compute mean returns, volatility, and raw Sharpe ratios. Second, we look at the excess return decompositions for each decile against the one- and four-factor (FF4)[15] models. While we run the one-factor regression across the entire period under observation (178 months from January 2007 to October 2021), due to the limitation of the IIMA Fama French Library, we run the FF4 from January 2007 to March 2021, a total of 172 months. The FF4 analysis provides a robust empirical framework to determine if indeed long-only portfolios have factor exposures. *A priori*, by using the Database for the Indian Market as the control, each factor portfolio should demonstrate statistically significant exposures to the underlying factors.

The persistence of factors is an important operational consideration in the rebalancing frequency of a systematic factor-based portfolio. We trace the change in the subsequent portfolio deciles of all the constituents in the winner portfolio over time. At $t = 0$, all the constituents of the top decile will have a score of 10 by construction. We look at how the constituents decile scores decay over time $t = t{+}1$, $t{+}2$, $t{+}3$, ..., $t{+}12$, $t{+}24$, and $t{+}36$ months. As the factor strength dissipates, the portfolio score[16] will drop below 10. These trajectories of scores evidence the persistence of the factors over time[17]. We us the results from the FF4 analysis and the trajectories to ask what are reasonable hold periods for systematic long-only factor strategy portfolios.

Factors expose investors to different risks. Inherently, academic factors have a low correlation with each other. However, our long-only factor-tilt portfolios have market exposure. Hence, to explore the diversification benefits between them, we compute correlations of returns. Since our universe is constrained to the top 200 stocks by market capitalization, there is a chance that the same stocks appear in many factor portfolios, reducing diversification benefits. To extend the returns-based analysis, we break down the winner portfolios into their size and sector categories to measure differences in size and sectoral exposure in each strategy.

The S&P BSE 200 constituents, by definition, are skewed in size. To determine 'Big' and 'Small' size categories, we could either split the S&P BSE 200 into the top 100 and the bottom 100 following the Securities and Exchange Board of India's categorisation of firms as the universe for 'Large Cap' funds[18] or follow Edwards and Cavalli-Sforza (1965) suggestion that the best split of observations into two clusters is one which minimizes the within-group sum of squares or maximizes the between-group sum of squares. Following the latter, we checked for various split-points from the 40$^{\text{th}}$ to the 70$^{\text{th}}$ percentile in steps of 5 percentile points and found that the within-group sum of squares and the between-group sum of squares were best configured

[15]the standard Fama French Four Factors - Market, Size, Value, and Momentum. (Fama and French, 1993; Carhart, 1997)

[16]an equal-weighted average of scores of each of the constituents of original winner portfolio.

[17]Another approach is to look at the probabilities of persistence over time for each constituent of the winner portfolios. The results will be similar to the approach we follow.

[18]https://www.amfiindia.com/Themes/Theme1/downloads/1507291273374.pdf

Table 1: Market Capitalisation of Firms

	Mkt Cap Breakpoint (Rs. Cr)
2006-12-31	7,000
2007-09-30	7,200
2008-09-30	8,600
2009-09-30	7,100
2010-09-30	14,600
2011-09-30	10,300
2012-09-30	9,800
2013-09-30	10,500
2014-09-30	16,600
2015-09-30	24,100
2016-09-30	24,100
2017-09-30	28,000
2018-09-30	31,200
2019-09-30	32,200
2020-09-30	33,700
2021-09-30	46,600

This table shows the cross-sectional market capitalisation breakpoints annually and the number of firms classified as 'Big' as at the end of September annually. New entrants to the constituent list will be categorised based on the market capitalisation on entry month and that categorisation will be refreshed in the following September. The market capitalisation values are round to the nearest hundred crores.

at 60%. A firm's market capitalization is its average market capitalisation at the end of each month between October of the prior year and September of the calculation year. All stocks are classified as 'Big' (B) and 'Small' (S) based on the average market capitalisation in September of every year[19]. Table 1 summarises the breakpoints, and Table 2 the median number of firms classified as 'Big' and 'Small' across our observation period.

Table 2: Median Number of Firms by Size

	Big	Small
Size	90	111

This table shows the median number of firms across the entire observation period classified as 'Big' or 'Small'. The sum of the two median values might not add to 200.

Table 3: Median Sector Allocation of S&P BSE 200

	Pct Share
Financials	20.7
Basic Materials	13.6
Consumer Cyclicals	13.1
Industrials	11.6
Healthcare	9.1
Consumer Non-Cyclicals	8.6
Technology	8.6
Energy	6.6
Utilities	6.1
Real Estate	2.0

This table shows the median share of each sector calculated by the TRBC Economic Sector of each constituent firm within the Index at the end of each month across the entire observation period. The share is calculated on an equal weight basis rather than the traditional market cap basis. Due to rounding, the total may not be exactly 100%.

The Refinitiv Business Classification (TRBC) schema[20] is used to categorise all firms into 10 economic

[19]For the period from December 2006 through to end September 2007, we used the December 2006 market caps to derive the breakpoint and the starting categorisation.

[20]Covering over 250,000 securities in 130 countries, TRBC is a global, comprehensive, industry classification system owned and operated by Refinitiv. See https://www.refinitiv.com/content/dam/marketing/en_us/documents/fact-sheets/trbc-business-classification-fact-sheet.pdf

sectors: Basic Materials, Consumer Cyclicals, Consumer Non-Cyclicals, Energy, Financials, Healthcare, Industrials, Real Estate, Technology, Utilities. For all the portfolios formed, we compute the sectoral allocation and compare these between the portfolios and the S&P BSE 200 index constituents. As we use equal-weighted weights for the portfolios, the S&P BSE 200 sector comparison is also done on an equal weight basis. Table 3 shows the median share of each sector computed on the number of firms classified by their sector for the constituents of the index every month.

Table 4 outlines the factor strategies we have chosen and their definitions. Size, value, momentum and low volatility are referenced primarily from academic research. For high beta, growth and quality, we adapt popular 'strategy-index' approaches by leading index providers. There are more sophisticated ways of defining each factor. We deliberately keep the definitions as simple as possible for this study. To be clear, we are not attempting to replicate any earlier research or index methodology

Table 4: Factor descriptions

Factor	Label	Metric Used	Score	Portfolio Construction	Source
Size	SIZE	Market Cap	$zscore\left(\frac{1}{MktCap_{M-1}}\right)$	Based on market cap as of the last trading day of the previous month	Fama and French (1993)
Value	VAL_ac	Book to Market	$zscore\left(\frac{B_{M-3}}{P_{M-1}}\right)$	Book value from most current reported results with 3 month lag, Market Price as of last trading day of previous month.	Fama and French (1993)
Value	Val_mf	1. Book to Market 2. Price to Earnings 3. Return on Capital Employed 4. Dividend Yield	$0.4 \times zscore\left(ROCE_{M-3}\right) + 0.3 \times zscore\left(-\frac{P_{M-1}}{E_{M-3}}\right) + 0.2 \times zscore\left(-\frac{P_{M-1}}{B_{M-3}}\right) + 0.1 \times zscore\left(P_{M-1}/Dividends_{M-3}\right)$	Book value, earnings, capital employed and Dividends paid all from most current reported results lagged by 3 month. Prices from last trading day of previous month.	Adapted from Index Provider
Momentum	MOM_ac	Price Momentum (12 months skip current month)	$zscore\left(\frac{P_{M-1}}{P_{M-12}} - 1\right)$	$P_{M-1}/P_{M-12} - 1$ from current month	Jegadeesh and Titman (1993)
Momentum	MOM_vol	Price Momentum adjusted by daily vol (combination of 13 month and 7 month price momentum adjusted by daily return std deviation for the 13 month period)	$0.5 \times zscore\left(\frac{P_{M-1}}{P_{M-13}} - 1\right)/\sigma_{\text{daily prices}_{t=M-13}^{M-1}} + 0.5 \times zscore\left(\frac{P_{M-1}}{P_{M-7}} - 1\right)/\sigma_{\text{daily prices}_{t=M-13}^{M-1}}$	13 month and 7 month price momentum adjusted by standard deviation of daily log returns over 13 months	Adapted from Index Provider
Low Volatility	LOVOL	12 month daily price log return volatility from M-1 to M-13	$zscore\left(1/\text{Std Dev}\left(log\left(\frac{P_t}{P_{t-1}}\right)\right)_{t=M-13}^{M-1}\right)$	12 months daily prices from last trading day of previous month	Adapted from Index Provider and Ang et al. (2006)
Betting against Beta	BAB	Beta Computed using rolling 1 year daily standard deviations and rolling five-year three-day correlations and shrunk using Frazzini and Pedersen (2014); Agarwalla et al. (2014)	$zscore(1/BAB)$	5 years daily prices from last trading day of previous month	Frazzini and Pedersen (2014); Agarwalla et al. (2014)
Beta	BETA	Beta computed using CAPM regression and 1 year price returns of stock and S&P BSE 200 where β comes from $(r_{stock} - rf) = \alpha + \beta \times (RM - rf)$	$zscore(beta)$	12 months daily prices from last trading day of previous month	Adapted from Index Provider
Growth	GROW	1. Three-Year Net Change in Earnings per Share over Price 2. Three-Year Growth in Revenue from Business Activity 3. Momentum (MOM_ac)	$\frac{1}{3} \times zscore\left(\frac{EPS_{M-3}-EPS_{M-39}}{P_{M-1}}\right) + \frac{1}{3} \times zscore\left(\frac{Rev_{M-3}-Rev_{M-39}}{P_{M-1}}\right) + \frac{1}{3} \times zscore\left(\frac{P_{M-1}}{P_{M-12}} - 1\right)$	EPS and Revenue from Business activity from most current reported results lagged by 3 month, Market Price as of last trading day of Previous month.	Adapted from Index Providers
Quality	QUAL	1. ROE 2. Debt to Equity 3. EPS growth variability (window = 5 years, min period = 3 years)	Financial companies : $0.5 \times zscore(ROE) + 0.5 \times zscore(-\sigma_{EPSgrowth})$ Non Financial Companies : $0.33 \times zscore(ROE) + 0.33 \times zscore(-DE) + 0.33 \times zscore(-\sigma_{EPSgrowth})$	Using ROE, DE and EPS values lagged by 3 months prior to current date	Adapted from Index Provider

We have deliberately chosen alternate methodologies for some factors (value, momentum, low volatility) to explore the differences in outcomes arising from the design choice. Additionally, for some strategies we use a multi-parameter approach[21]. In all cases, we calculate the underlying factor exposure using a consistent calculation method. For instance, we apply a 3-month lag for accounting metrics from the month first appearing on Refinitiv consistently. So, if EPS was reported on Refinitiv at the end of March 2018, it will only be included effective June 2018.

[21] Using multiple parameters and optimising within the chosen parameter is one popular method used by managers for factor strategies. It is prone to 'p-hacking' or 'over-fitting'.

We use z-scores to normalise the variables before we rank firms and create decile portfolios:

$$z = \frac{x_i - \mu}{\sigma} \tag{1}$$

where x_i is the value for firm i, μ is the mean for the variable across all constituent firms for the month, and σ is the standard deviation of the variable across all constituent firms for the month. We further transform the z-score to deal with negative values as follows :

$$z = \begin{cases} (1+z) & \text{if } z \geq 0 \\ \frac{1}{1-z} & \text{if } z < 0 \end{cases} \tag{2}$$

All stocks in the universe for the month are ranked on z-scores and the ranks are used to create the decile portfolios.

We compute rolling alphas using the practitioner definition :

$$\alpha_i = \left(\left(1 + \frac{P_{m,i}}{P_{m-t,i}}\right)^{1/t} - 1 \right) - \left(\left(1 + \frac{BSE200_m}{BSE200_{m-t}}\right)^{1/t} - 1 \right) \tag{3}$$

where i is factor i, $P_{m,i}$ is the NAV for the portfolio for factor i as at end of month m, $P_{m-t,i}$ is the NAV for the same portfolio t years prior (t = 3, 5) and $BSE200_m$ and $BSE200_{m-t}$ is the value of the S&P BSE 200 at the end of months m and $m - t$ respectively.

The one factor (CAPM) model uses the S&P BSE 200 as the market and is described by:

$$r_i - r_f = \alpha + \beta \times (R_{BSE200} - r_f) + \epsilon \tag{4}$$

where r_i is the return for factor portfolio i, r_f is the risk-free rate, R_{BSE200} is the return for the S&P BSE 200 index. All periods are monthly periods. As the winner portfolios are not market neutral, the size of market β will inform the contribution of the market excess returns to explain the factor portfolio excess returns.

The four-factor Fama French model uses the factors from the Data Library for Indian Market and is described by :

$$r_i - r_f^{IIMA} = \alpha + \beta_{MKT} \times MKT^{IIMA} + \beta_{SMB} \times SMB + \beta_{HML} \times HML + \beta_{WML} \times WML + \epsilon \tag{5}$$

where r_i is the return for factor portfolio i, r_f^{IIMA} is the risk-free rate in the Data Library, MKT^{IIMA} is the market factor from the library, SMB is the size factor (Small-minus-Big), HML is the value factor (High-minus-Low), and WML is the momentum factor (Winner-minus-Loser). All periods are, again, monthly. We are interested in the coefficients of all the factors as well as the α. A portfolio needs to show statistically significant relevant βs to demonstrate factor exposure. Hunstad and Dekhayser (2015) proposed a factor efficiency ratio (FER). We calculate a modified FER for factor i, f_i:

$$FER_i = \frac{f_i}{\sum_{k \neq i} |f_k|} \tag{6}$$

where $|f_k|$ is the absolute exposure from the $\mathrm{k^{th}}$ undesired factor. The higher the FER, the more efficient the fund is at gaining desired factor exposure. As we expect the long-only portfolios to show exposure to MKT, we also compute FER excluding the MKT factor. Both metrics will inform the factor exposure. As the Data Library for Indian Market only consists of SMB, HML and WML, we compute the FER for size, value and momentum winner portfolios.

Turnover of factor strategies is a well-researched topic. We do not seek to optimise the implementation to reduce turnover. Consequently, the turnover rates of portfolios in our study are probably higher than any real-world strategies. The Securities and Exchange Board of India's definition of turnover[22] is used to compute turnover:

$$Turnover = \frac{\min\left(\sum_{n=1}^{t} Sales_t, \sum_{n=1}^{t} Purchases_t\right)}{\frac{\sum_{n=1}^{t} AuM_t}{N}} \tag{7}$$

where $\sum_{n=1}^{t} Sales_t$ is the total value of sales over period $n = 1, ..t$ and $\sum_{n=1}^{t} Purchases_t$ is the total value of purchase the same period, and $\frac{\sum_{n=1}^{t} AuM_t}{N}$ is the average Assets under Management for the period. We express turnover as a percentage. Each portfolio has two drivers of total sales/purchases for a period. First, the sales/purchases related to the rebalancing required to maintain the equal weight. Second, the sales/purchases related to the changes in constituents. We can use equation 7 to calculate the turnover related to rebalancing and that related to new constituents.

$$Turnover_{total} = Turnover_{rebalancing} + Turnover_{new} + \epsilon \tag{8}$$

where $Turnover_{total}$ is the turnover using the aggregate of all purchases and sales for the period, $Turnover_{rebalancing}$ is the turnover related to the purchases and sales required for rebalancing for the same period, $Turnover_{new}$ is the turnover related to the purchases and sales required from changing constituents for the same period. The min method may create a small difference in the sum of the two sub-turnovers and the total turnover for a period due to the different rates of return within the individual constituents leading to small differences, especially in the rebalancing related turnover.

While we ignore costs for most part, we estimate the shrinkage arising from implementation[23]. We use turnover and size splits of portfolios to estimate shrinkage of returns due to implementation. Brokerage costs have declined rapidly in recent years in India due to increased competition, adoption of technology-enabled

[22] the lower of sales or purchase divided by the average Assets under Management for the period.
[23] We ignore taxes entirely.

market infrastructure (including payments, clearing, custodial, and reporting services), and rise of technology-enabled low/no-cost brokerages amongst other reasons. We estimate these to be in the region of 10-30 basis points per leg and use a 20 bps cost per leg of a trade. We estimate impact costs based on the size of the firm, using the Nifty Impact cost data[24] to build a simple model of impact cost. For firms classified 'Big', we estimate a 5bps impact cost, and for all other firms, we estimate a 30 bps impact cost. Brokerage costs are the cost of 2 legs of the average number of constituents changed every month in the winner factor portfolio. Impact costs are calculated as the sum of the 2 legs of impact spreads for 'Big' and 'Small' firms multiplied by the average size splits for each winner portfolio over the period.

By being conservative in our estimate of costs (both brokerage and impact) and implementing an EW monthly rebalanced portfolio methodology, which will likely have higher turnover than optimised implementation, our estimate for costs will be at the higher end of the possible range of implementation costs. If positive alpha exists under these conditions, we are reasonably confident that real-world implementations with more sophisticated implementation choices to optimise turnover and impact costs can generate higher expected alphas over the long term.

3.2 Data

All our data is from Refinitiv and Datastream. The S&P BSE 200 constituents are from Datastream. The constituent dataset is available from December 2006. Constituents are updated monthly from 2011 and at 6 monthly intervals between 2006 and 2011. There is no survivorship bias in the constituent list as we cover all firms including those that were de-listed or amalgamated/merged subsequently. We get daily closing prices of all the firms in our universe[25]. Market capitalization for all firms are as of the month-end[26]. Price-to-Book (PB), Price-to-Earnings (PE), and Dividend Yields (DY) for all firms is as of every month end. The values are lagged by 3 months to avoid forward-looking bias. The price for the PB, PE, DY are adjusted using the firm's closing price for the previous month divided by the firm's closing price from 3 months ago to reflect the adjustment in the PB, PE, and DY values. As a result, we ensure a consistent 3 month lag in the accounting values reported by the firm, while adjusting the price for the measurement period. Annual Revenue from Business Activity, Return on Capital Employed (ROCE), Return on Equity (ROE), Earnings per Share (EPS), and Debt Equity Ratio (DE) are annual from financial statement data on Refinitiv. These are also lagged by 3 months for our calculations. For both the annual and monthly fundamental accounting variables, we recognize that different firms are on different reporting cycles. Every month we take the most current lagged variables available. Across

[24] The impact costs for the Nifty 50 stocks for a portfolio of ₹50 lacs is, on average, 2bps (range from 1-10bps). For a ₹25 lacs portfolio size in the Next 50 is, on average, 8bps (range 2bps to 210 bps) (Data for 2021 from Nifty Indices https://www.niftyindices.com/reports/monthly-reports

[25] We have prices for all except for one stock. This stock entered the S&P BSE 200 in 2021 and would not be included in any factor portfolio during our observation.

[26] We have 4 firms for which we do not have market-cap data for some months. Using secondary research, we have classified these as 'Small' firms. Unfortunately, these firms are excluded from the size factor calculations for the relevant months. Therefore, there is very little survivorship bias in our accounting dataset.

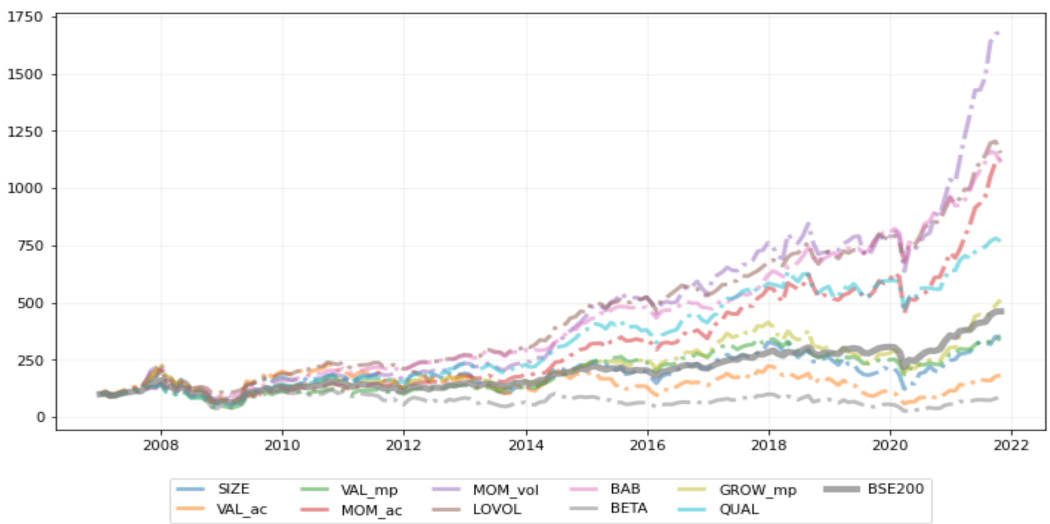
the year, every firm will have reported their results[27] and therefore would be accounted for in the portfolios.

We use survivorship-bias adjusted monthly data from Fama French and Momentum Factors: Data Library for Indian Market(Agarwalla et al., 2013) with data till March 2021 as our FF4 dataset. The risk-free rate is computed using the 91-days T-bill rate sourced from the Reserve Bank of India's weekly auction data available at Refinitiv[28]. The implied yields are converted to daily and monthly rates. Our method is the same as followed by Agarwalla et al. (2013).

4 Results and Discussion

Figure 1 shows the development of the wealth index (Dec 2006=100) for the winner portfolios across the various factor styes. Over the observation period, many, but not all, of the winner portfolios outperform the S&P BSE 200 (shown in grey). This chart is similar to those found in the marketing materials of factor tracker strategies. Unfortunately, it does not tell the whole story and, as we show, actually says very little.

Figure 1: Wealth Index of Winner Long-only Factor Portfolios: Jan 2007 to Oct 2021



Source: Authors calculations, Refinitiv.

4.1 Winner Portfolio Rolling Alphas

We compute rolling alphas for the winner portfolios for each of our factor strategies. Our preferred metric is mean rolling alphas to minimise the 'point-in-time' bias. Alphas are computed using equation 3 as rolling 3- and 5-years means using monthly returns. Table 5 summarises the alphas. Seemingly, other than size, one flavour of value, the high beta factor and growth, all the other winner portfolios generate significant positive mean 3- and 5-year alphas relative to the S&P BSE200 Index.

[27]There are cases where firms have changed their reporting cycle. This is a matter of routine, and we, therefore, treat the accounting variables as they get reported. While Refinitiv provides standardised data, in the case of other sources, the data may need to be first normalised.

[28]The data is also available at http://dbie.rbi.org.in/DBIE/dbie.rbi?site=statistics, under Financial Market» Government Securities Market.

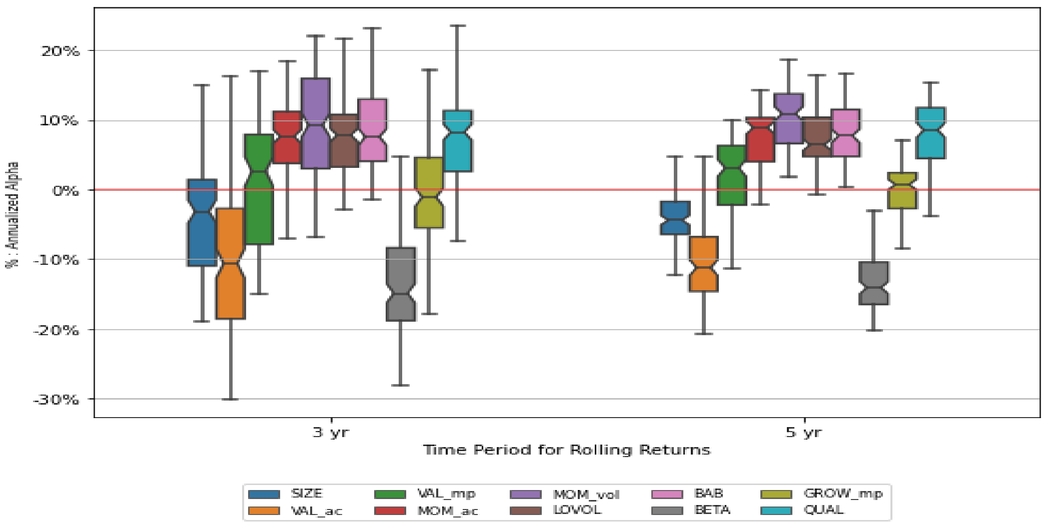
Table 5: Mean Annualised 3 and 5 year rolling Alpha Winner Long-only Factor Portfolios: Jan 2007 to Oct 2021

	3 yr	5 yr
SIZE	-3.7	-3.7
VAL_ac	-9.6	-10.4
VAL_mp	0.4	1.6
MOM_ac	6.5	7.6
MOM_vol	9.4	10.3
LOVOL	7.7	7.4
BAB	8.5	8.1
BETA	-13.9	-13.7
GROW_mp	-0.8	-0.0
QUAL	7.1	7.6

This table shows the **annualised** rolling alpha computed for each winner portfolio over the returns of the S&P BSE 200 Index.

Figure 2 shows the range of the rolling returns. On average 3- years alphas have a wider 5-year alphas: *the longer the period of following any systematic, the realised returns are converge closer to average returns.* Amongst all the factors, low volatility winner portfolios have the narrowest range of alpha over the 3- and 5-year periods. The range over 5-years for momentum is also relatively narrow compared to other factors. In general, the range of alpha is wide. Depending upon the entry timing, an investor could experience a negative or positive 3-year alpha. Across all strategies, for our observation period, an unfortunate investor entering at the worst time would experience negative alphas over 3-years. Over 5-years, only MOM_vol and BAB winner portfolios would have outperformed the broader market for the same hapless investor. However, the maximum 3- and 5-year alphas are positive across all strategies except for 5-year BETA. Empirically, *entry timing does play a role in realised alpha across strategies even over "long" periods*[29]. Factor strategies can under perform, even over "long" periods.

Figure 2: Rolling 3 and 5 years Annualised Alphas Ranges for Winner Long-only Factor Portfolios: Jan 2007 to Oct 2021



Source: Authors calculations, Refinitiv. All alphas are excluding any costs.

Rolling alphas offer a better picture of the potential attractiveness of factor style portfolios. Different style

[29]In India, 3 years is often seen as an eternity amongst many investors and advisers.

have different inherent volatility. Shorter holding periods are more volatile than longer holding periods. Different styles have different risk and we turn next to risk-adjusted returns.

4.2 Long-only Systematic Decile Portfolios: Risk-adjusted returns

Table 6: Gross Annualised Returns and Risk Across Deciles for different Long-only Factor Portfolios: Jan 2007 to Oct 2021

		D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9	D_10
SIZE	Mean	13.63	9.67	13.62	17.99	20.40	16.49	15.24	14.88	20.34	18.06
	std	22.34	25.84	25.74	27.91	27.66	27.25	29.97	33.13	34.95	41.89
	Raw Sharpe	0.61	0.37	0.53	0.64	0.74	0.61	0.51	0.45	0.58	0.43
VAL_ac	Mean	16.47	18.72	16.92	17.03	15.61	13.26	17.34	15.68	16.19	13.62
	std	22.65	23.42	23.50	26.53	28.12	30.36	29.71	36.10	37.52	42.74
	Raw Sharpe	0.73	0.80	0.72	0.64	0.56	0.44	0.58	0.43	0.43	0.32
VAL_mp	Mean	12.38	9.02	16.59	16.68	19.97	16.05	16.11	20.17	20.10	13.06
	std	35.15	30.49	28.57	29.34	27.05	29.39	29.20	30.34	28.26	29.18
	Raw Sharpe	0.35	0.30	0.58	0.57	0.74	0.55	0.55	0.66	0.71	0.45
MOM_ac	Mean	13.71	13.67	15.56	11.10	14.95	14.49	18.43	19.16	16.76	22.35
	std	45.08	37.34	34.84	31.93	27.53	26.94	23.59	24.12	24.48	26.99
	Raw Sharpe	0.30	0.37	0.45	0.35	0.54	0.54	0.78	0.79	0.68	0.83
MOM_vol	Mean	10.77	10.40	14.44	11.58	14.72	17.25	16.19	18.84	21.18	24.99
	std	38.25	35.37	33.10	32.82	31.30	29.43	26.05	24.94	24.80	25.71
	Raw Sharpe	0.28	0.29	0.44	0.35	0.47	0.59	0.62	0.76	0.85	0.97
LOVOL	Mean	7.83	18.12	19.79	18.21	14.90	14.60	16.78	13.68	17.05	19.28
	std	47.14	39.21	36.34	34.22	28.91	26.96	24.39	23.53	21.48	15.26
	Raw Sharpe	0.17	0.46	0.54	0.53	0.52	0.54	0.69	0.58	0.79	1.26
BAB	Mean	14.44	9.82	13.67	19.43	18.35	17.28	14.65	15.82	18.85	18.88
	std	48.40	37.74	34.30	31.91	30.00	28.84	24.82	23.90	21.66	16.02
	Raw Sharpe	0.30	0.26	0.40	0.61	0.61	0.60	0.59	0.66	0.87	1.18
BETA	Mean	20.49	18.90	17.32	17.26	17.48	16.62	13.56	11.51	15.35	11.58
	std	15.73	22.59	24.81	26.83	27.70	28.94	29.74	35.24	39.20	49.66
	Raw Sharpe	1.30	0.84	0.70	0.64	0.63	0.57	0.46	0.33	0.39	0.23
GROW_mp	Mean	15.25	16.09	14.28	12.17	10.74	15.17	21.58	18.80	18.38	17.70
	std	40.55	34.56	33.48	27.62	27.89	24.67	25.50	25.73	26.94	31.69
	Raw Sharpe	0.38	0.47	0.43	0.44	0.38	0.62	0.85	0.73	0.68	0.56
QUAL	Mean	10.96	16.70	16.44	9.88	16.32	16.25	18.96	17.35	20.99	17.33
	std	36.76	33.11	32.73	31.57	28.01	26.44	26.08	23.90	25.53	24.14
	Raw Sharpe	0.30	0.50	0.50	0.31	0.58	0.61	0.73	0.73	0.82	0.72

This table shows the **annualised** mean return for each decile (D_1 being the lowest or worst and D_10 being the highest or best ranked firms) across each of the factors in Table 4, the annualised standard deviation of the returns and raw Sharpe Ratio.

Ideally, if factors affect performance, returns should increase monotonically across the deciles. Table 6 shows **annualised** gross returns, annualised standard deviation and raw Sharpe Ratio for decile portfolios across all styles. The S&P BSE 200 had an annualised mean return of 13.89%, an annualised standard deviation of 23.25 and a raw Sharpe of 0.6. Momentum and low-volatility show moderate to strong monotonic increases in raw Sharpe across deciles. High Beta shows a generally reducing raw sharpe from the loser decile to the winner decile. Value's raw Sharpe does not have a clear trend and varies between the two variants[30]. Size, reflective of the relative growth of returns in large-cap firms during the current decade, shows a downward trend in the raw Sharpe ratio across the deciles. Growth and quality show increasing raw Sharpe ratios across deciles, but the path is not linear. The lowest decile portfolio for all factors has a positive return during our observation period. With the caveats of the universe, the S&P BSE 200, the construction method, and the observation period empirically *on average, shorting a naive loser portfolio is a losing proposition.*

[30]VAL_ac shows a weakening raw Sharpe to a lesser degree. VAL_mp has a more complex raw Sharpe trajectory.

Across factors, risk generally improves over deciles. The higher deciles for multi-parameter value, momentum, low-volatility, growth, and quality show lower standard deviations in the highest decile compared with the lower deciles. Size, as expected, shows higher risk in D_10 (small cap) compared with D_1 (large cap). As the decile portfolios have only 20 stocks, one would expect the standard deviation of returns of top decile portfolios to be higher than the much broader S&P BSE 200 Index. Interestingly, the standard deviation of returns for the low volatility winner portfolios is significantly lower than the S&P BSE 200 index. For a 20-stock portfolio to have significantly lower volatility while delivering higher expected returns should be of interest to asset allocators and researchers. For the winner portfolios of momentum, the standard deviations of returns are higher than that of the S&P BSE 200 Index, but not by very much.

Across the style winner portfolios, size, value and, more marginally, growth under-perform the index in raw Sharpe terms. Winner portfolios for other styles have superior risk adjusted returns during our observation period.

A small digression on how we present decile portfolio for the styles. We have adopted the convention that winner portfolios across styles are portfolios of firms showing the highest z-scores for the characteristic. Thus, the winner portfolios for size would be the smallest firms; the 'cheapest' firms for value; the highest momentum firms for momentum; the lowest volatility for low volatility; the highest beta for beta; the firms showing the highest growth for growth and the firms with the highest z-scores across our quality characteristics for quality. Some researchers present findings such that low-volatility and high beta styles are ordered in the same manner - where the highest decile shows the highest volatility and the highest beta. For readers more used to the other method, the 'inverted' Beta factor is another version of low volatility[31].

4.3 Long-only Systematic Decile Portfolios: One Factor Analysis

Taking a more formal analytical approach, we regress the excess returns of each of the decile portfolios against the S&P BSE 200 excess returns. Table 7 summarises this analysis. First, we look at α. The higher decile portfolios for momentum and low volatility have a statistically significant positive intercept (α). The annualised α for momentum is between 7% and 10% and approx 7% for low-volatility. Between the two variations in momentum, MOM_vol shows a stronger statistical α than MOM_ac with the top 3 deciles of MOM_vol showing statistically significant and positive α. The top two decile portfolios of both variations of low volatility[32] also have statistically significant and positive α. For increasing deciles for quality and growth, α generally increases. However, the statistical significance is less clear. The value portfolios do not exhibit any statistically significant trend. Loser portfolios across all styles do have statistical evidence of negative α. Once again, *going short loser portfolios is not statistically likely to generate positive expected returns* for our universe and the observation

[31]Such readers will need to read the BETA row from right to left instead of left-to-right for the other factors for the low-volatility interpretation.

[32]as well as the lowest two decile portfolios of BETA.

Table 7: One Factor Regression Summary for Long-only Factor Portfolios: Jan 2007 to Oct 2021

		D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9	D_10
SIZE	Intercept	0.01	-0.36**	-0.05	0.23	0.41*	0.14	-0.00	-0.10	0.27	-0.02
		(0.09)	(0.14)	(0.17)	(0.22)	(0.23)	(0.23)	(0.26)	(0.28)	(0.34)	(0.44)
	MKTRF	0.94***	1.08***	1.06***	1.12***	1.10***	1.08***	1.18***	1.31***	1.34***	1.58***
		(0.01)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.05)	(0.07)
	R-squared	0.97	0.94	0.91	0.87	0.85	0.85	0.84	0.85	0.80	0.77
	Adj. R-squared	0.97	0.94	0.91	0.87	0.85	0.85	0.84	0.85	0.80	0.77
VAL_ac	Intercept	0.27	0.39**	0.25	0.18	0.05	-0.17	0.15	-0.10	-0.07	-0.35
		(0.23)	(0.19)	(0.19)	(0.19)	(0.22)	(0.23)	(0.24)	(0.33)	(0.38)	(0.47)
	MKTRF	0.86***	0.93***	0.94***	1.08***	1.13***	1.22***	1.18***	1.41***	1.42***	1.58***
		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.05)	(0.06)	(0.07)
	R-squared	0.78	0.86	0.87	0.89	0.87	0.88	0.86	0.83	0.78	0.74
	Adj. R-squared	0.78	0.86	0.87	0.89	0.87	0.88	0.86	0.83	0.78	0.74
VAL_mp	Intercept	-0.31	-0.48*	0.12	0.10	0.39*	0.06	0.07	0.33	0.37*	-0.14
		(0.35)	(0.26)	(0.23)	(0.23)	(0.22)	(0.24)	(0.23)	(0.24)	(0.22)	(0.27)
	MKTRF	1.34***	1.20***	1.14***	1.18***	1.08***	1.17***	1.17***	1.22***	1.14***	1.13***
		(0.05)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)
	R-squared	0.79	0.84	0.86	0.87	0.86	0.86	0.87	0.87	0.87	0.82
	Adj. R-squared	0.79	0.84	0.86	0.87	0.86	0.86	0.87	0.87	0.87	0.81
MOM_ac	Intercept	-0.38	-0.26	-0.08	-0.35	0.02	-0.02	0.35**	0.41**	0.24	0.61**
		(0.52)	(0.37)	(0.32)	(0.29)	(0.22)	(0.18)	(0.17)	(0.20)	(0.23)	(0.30)
	MKTRF	1.65***	1.43***	1.36***	1.25***	1.11***	1.11***	0.96***	0.96***	0.95***	0.99***
		(0.08)	(0.05)	(0.05)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
	R-squared	0.72	0.79	0.83	0.83	0.87	0.91	0.89	0.85	0.82	0.74
	Adj. R-squared	0.72	0.79	0.83	0.83	0.87	0.91	0.89	0.85	0.82	0.73
MOM_vol	Intercept	-0.48	-0.46	-0.12	-0.35	-0.08	0.15	0.14	0.35**	0.53**	0.83***
		(0.41)	(0.35)	(0.31)	(0.25)	(0.26)	(0.25)	(0.20)	(0.17)	(0.21)	(0.31)
	MKTRF	1.43***	1.35***	1.28***	1.32***	1.24***	1.17***	1.05***	1.02***	0.98***	0.93***
		(0.06)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.05)
	R-squared	0.76	0.79	0.81	0.88	0.86	0.85	0.88	0.90	0.85	0.70
	Adj. R-squared	0.76	0.79	0.81	0.88	0.86	0.85	0.88	0.90	0.85	0.70
LOVOL	Intercept	-0.92**	0.00	0.16	0.12	-0.02	-0.00	0.22	0.02	0.31*	0.64***
		(0.46)	(0.35)	(0.27)	(0.30)	(0.22)	(0.20)	(0.18)	(0.18)	(0.17)	(0.17)
	MKTRF	1.81***	1.54***	1.47***	1.34***	1.16***	1.09***	0.99***	0.95***	0.86***	0.57***
		(0.07)	(0.05)	(0.04)	(0.05)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
	R-squared	0.80	0.84	0.89	0.83	0.87	0.89	0.88	0.87	0.87	0.74
	Adj. R-squared	0.80	0.84	0.89	0.83	0.87	0.89	0.88	0.87	0.87	0.74
BAB	Intercept	-0.43	-0.59*	-0.21	0.24	0.21	0.16	0.06	0.18	0.46**	0.61***
		(0.50)	(0.32)	(0.30)	(0.25)	(0.25)	(0.24)	(0.21)	(0.21)	(0.23)	(0.20)
	MKTRF	1.82***	1.50***	1.35***	1.28***	1.20***	1.15***	0.99***	0.94***	0.82***	0.56***
		(0.07)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
	R-squared	0.77	0.85	0.84	0.87	0.86	0.86	0.86	0.83	0.77	0.66
	Adj. R-squared	0.77	0.85	0.84	0.87	0.86	0.86	0.86	0.83	0.77	0.66
BETA	Intercept	0.74***	0.44**	0.26	0.21	0.20	0.11	-0.14	-0.40	-0.19	-0.70
		(0.21)	(0.22)	(0.21)	(0.22)	(0.23)	(0.22)	(0.22)	(0.30)	(0.35)	(0.46)
	MKTRF	0.54***	0.87***	0.98***	1.07***	1.10***	1.16***	1.20***	1.40***	1.53***	1.93***
		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.05)	(0.07)
	R-squared	0.63	0.81	0.85	0.86	0.86	0.87	0.88	0.85	0.83	0.82
	Adj. R-squared	0.63	0.80	0.85	0.86	0.86	0.87	0.88	0.85	0.83	0.82
GROW_mp	Intercept	-0.20	-0.03	-0.14	-0.19	-0.30	0.09	0.53***	0.34*	0.29	0.15
		(0.42)	(0.33)	(0.31)	(0.21)	(0.22)	(0.17)	(0.18)	(0.20)	(0.23)	(0.29)
	MKTRF	1.53***	1.34***	1.30***	1.11***	1.12***	1.00***	1.04***	1.03***	1.07***	1.23***
		(0.06)	(0.05)	(0.05)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
	R-squared	0.78	0.81	0.82	0.88	0.87	0.89	0.89	0.87	0.85	0.82
	Adj. R-squared	0.78	0.81	0.81	0.88	0.87	0.89	0.89	0.87	0.85	0.82
QUAL	Intercept	-0.47	0.04	0.01	-0.45*	0.11	0.14	0.35	0.28	0.50**	0.28
		(0.32)	(0.29)	(0.27)	(0.24)	(0.23)	(0.21)	(0.22)	(0.20)	(0.20)	(0.22)
	MKTRF	1.44***	1.30***	1.30***	1.27***	1.12***	1.06***	1.04***	0.95***	1.03***	0.95***
		(0.05)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
	R-squared	0.84	0.83	0.86	0.88	0.86	0.86	0.85	0.86	0.88	0.83
	Adj. R-squared	0.84	0.83	0.86	0.87	0.86	0.86	0.85	0.86	0.88	0.83

This table shows the summary of regression of the decile portfolio monthly excess returns against the monthly excess returns of the S&P BSE 200 Index. We show the Intercept and the MKTRF (excess returns of the Index). Standard errors in parentheses under each coefficient.
* $p<.1$, ** $p<.05$, *** $p<.01$

period.

Second, except for size and VAL_ac, in general, higher decile portfolios for momentum, low volatility, growth, and quality have lower betas than the lower decile portfolios. As noted above, low volatility strategies have significantly lower betas than the market - making these potentially attractive portfolios for certain types of investment strategies. The higher decile portfolios for momentum have betas below 1, but not by much. The increase in beta for size is aligned to evidence from other markets - small-cap stocks have a higher beta. In the Indian context, for the period under observation and the universe selected for the study, this additional risk taken due to firm size is not compensated by higher returns. In the case of value, we have a mixed picture - one method having an increase in beta as value deciles increase, and another demonstrating reduced beta. In both variations, beta is more than 1.

Finally, we look at r-square - how much of the excess returns of the decile portfolios are explained by the market. *A priori*, we would expect that both high deciles and low deciles to have lower r-squares than the central deciles to show the strength of the factor performance. Generally, except size, all other factors show evidence of lower r-squares at the extremes, and the r-squares of the top decile portfolios are at the lower end of the range of r-squares across deciles. R-squares range between 0.66 and 0.83 for the top decile portfolios and 0.63 and 0.97 for the bottom decile portfolios[33]. The low volatility factor has the lowest r-squares (0.66 for BAB and 0.74 for LOVOL) followed by momentum (0.70 for MOM_vol and 0.74 for MOM_ac). For size, the top-heavy nature of the S&P BSE 200, and hence the cap-weighted market indices, is seen in the high r-square for the loser portfolio for the category (0.97).

The one-factor return decomposition shows statistically significant and positive α for low volatility and momentum winner portfolios. For others, while there is no robust statistical α, there are encouraging signs such as low r-squares. Low volatility shows significantly lower beta than the S&P BSE 200 Index. Momentum, growth, and quality show marginally lower beta than the index. Surprisingly value portfolios, as defined, show significantly higher beta than the index.

4.4 Long-only Systematic Decile Portfolios: Fama French Four Factor Analysis

The Fama-French four-factor return decomposition shows the factor tilts of each of our long-only style portfolios. We use the Database for the Indian Market to decompose returns into four factors. We use the monthly survivorship-bias adjusted dataset of MKT (market), SMB (small-minus-big or size), HML (high-minus-low or value) and WML (winner-minus-loser or momentum) as the exogenous variables for our regression. The Database for the Indian Market uses a much larger universe than the S&P BSE 200. Table 8 summarises the results. In general, the FF4 decomposition explains more of the excess returns as seen by the larger r-squares than the one-factor decomposition (from mean r-square across all portfolios of 0.84 for one factor to 0.88 for FF4). The mean r-squares for the winner portfolios of each strategy are also higher (from 0.76 for one factor to 0.82 for FF4). The highest decile low volatility portfolios continue to show significantly lower r-squares (0.70 for BAB and 0.75 for LOVOL) compared to the r-squares of other winner portfolios.

If the FF4 decomposition shows a statistically significant exposure to the underlying factor, we would also

[33] The lowest BETA decile shows the lowest r-square. This is equivalent to the top deciles of the low volatility portfolios.

expect α in the FF4 analysis to be zero. Under this circumstance, the winner portfolios returns are well explained by the underlying factor. If there is a residual α, the FF4 does not fully explain the result and we would need to look for other exogenous variables. From our factor strategies, we would expect size, value and momentum to have no residual α while low volatility, beta, growth, and quality to have lower r-square and probably some α.

Mean MKT β across all decile portfolios reduces from 1.17 for one factor to 1.01 for FF4. The additional factors provide the increased explanatory power. *A priori*, each of our factor strategies should show statistically robust exposure to the relevant factor. As the portfolios are long-only, the specific factor βs will likely be less than 1. Our criteria to check for factor exposure for size, value and momentum strategies:

- The relevant factor exposure to be statistically significant for the winner and loser portfolios: a positive exposure for the winner portfolios and a negative exposure for the loser portfolios. At a minimum, the winner portfolios should have statistically significant factor β even if the loser portfolios do not show any exposure.
- There should be a progression from significant and negative underlying factor exposure at the loser portfolio to a significant and positive exposure for the winner portfolio. Towards the middle deciles, the factor exposure should dissipate. This trend of factor exposure is used in the analysis of persistence of the factor exposure.
- The relevant factor β is more than 0.20. This is an arbitrary cut-off point. We choose it as it implies that below this, less than a fifth of the change in 1% of returns is explained by the factor.
- α=0

The size portfolios show clear exposures to SMB under the first two criteria. The highest decile (the smallest market-cap firms in the S&P BSE 200 Index) has a positive and significant coefficient (0.41***) and the lowest decile (the largest caps in the 200 Index) show a negative and significant coefficient (-0.13***) to the SMB factor. The SMB exposure switches from positive to negative/zero between deciles 4 and 5. By decile 5, the exposure to SMB is less than 20% - and could serve as a point where we consider factor effect has effectively dissipated. The two extreme deciles also have opposite exposures to HML - the smallest caps have a positive and significant coefficient (0.22***). During our observation period and our universe, the small cap decile portfolio is more value biased. The higher decile portfolios all show negative and significant exposure to momentum (WML). As our size portfolios are split only on market-cap, this result implies that, for the observation period and our universe, the firms with the smallest market-caps in the S&P BSE 200 Index would be detractors in a momentum portfolio. For our third test, the winner portfolio has a significant and positive α. This result is contrary to the one-factor and the 3- and 5-year analysis.

Table 8: Four Factor Regression Summary for Long-only Factor Portfolios: Jan 2007 to Mar 2021

		D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9	D_10
	Intercept	-0.02	-0.33**	0.06	0.42*	0.57**	0.22	0.30	0.46*	0.88***	0.75**
		(0.13)	(0.16)	(0.18)	(0.24)	(0.22)	(0.23)	(0.26)	(0.24)	(0.27)	(0.33)
	MKTRF	0.93***	1.04***	0.95***	1.00***	1.00***	0.90***	0.98***	1.10***	1.06***	1.20***
		(0.02)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
	SMB	-0.13***	-0.07*	0.05	-0.04	0.15***	0.27***	0.30***	0.32***	0.34***	0.41***
		(0.03)	(0.04)	(0.04)	(0.06)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	(0.08)
SIZE	HML	-0.01	-0.02	0.06	0.12**	0.11**	0.18***	0.09*	0.02	0.08	0.22***
		(0.03)	(0.03)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.07)
	WML	-0.05**	-0.10***	-0.16***	-0.19***	-0.11***	-0.12***	-0.22***	-0.31***	-0.44***	-0.55***
		(0.02)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)	(0.06)
	R-squared	0.94	0.93	0.91	0.87	0.89	0.88	0.87	0.91	0.90	0.89
	Adj. R-squared	0.94	0.93	0.91	0.87	0.88	0.88	0.87	0.91	0.89	0.89
	Intercept	0.21	0.48**	0.28	0.38**	0.45**	0.32	0.64***	0.33	0.40	-0.05
		(0.22)	(0.20)	(0.20)	(0.18)	(0.21)	(0.21)	(0.21)	(0.28)	(0.35)	(0.38)
	MKTRF	0.91***	0.89***	0.89***	1.01***	1.00***	1.06***	0.99***	1.13***	1.08***	1.19***
		(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)	(0.06)	(0.06)
	SMB	0.15***	0.23***	0.20***	0.16***	0.15***	0.12**	0.11**	0.23***	0.16*	0.12
		(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.07)	(0.08)	(0.09)
VAL_ac	HML	-0.16***	-0.12***	-0.02	-0.05	-0.07	-0.04	0.06	0.24***	0.34***	0.62***
		(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.06)	(0.07)	(0.08)
	WML	0.08*	-0.02	-0.02	-0.12***	-0.26***	-0.33***	-0.35***	-0.36***	-0.44***	-0.43***
		(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)	(0.06)	(0.07)
	R-squared	0.83	0.87	0.88	0.92	0.90	0.91	0.92	0.89	0.85	0.86
	Adj. R-squared	0.83	0.87	0.88	0.92	0.90	0.91	0.91	0.89	0.85	0.85
	Intercept	-0.03	-0.51*	0.25	0.49**	0.59**	0.44*	0.43*	0.69***	0.71***	0.24
		(0.30)	(0.27)	(0.23)	(0.23)	(0.24)	(0.23)	(0.23)	(0.22)	(0.22)	(0.26)
	MKTRF	1.05***	1.05***	0.97***	0.99***	0.94***	1.03***	1.00***	1.07***	1.02***	1.01***
		(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
	SMB	0.21***	0.02	0.11**	0.19***	0.15***	0.19***	0.25***	0.21***	0.11**	0.19***
		(0.07)	(0.06)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)
VAL_mp	HML	0.30***	0.24***	0.20***	0.03	0.11**	0.00	0.05	0.00	-0.07	-0.04
		(0.06)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
	WML	-0.35***	-0.15***	-0.17***	-0.28***	-0.15***	-0.24***	-0.20***	-0.23***	-0.24***	-0.22***
		(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
	R-squared	0.87	0.86	0.89	0.90	0.87	0.90	0.90	0.91	0.90	0.86
	Adj. R-squared	0.87	0.85	0.88	0.89	0.86	0.89	0.89	0.90	0.89	0.86
	Intercept	0.69*	0.71***	0.67***	0.30	0.32	0.14	0.40**	0.23	-0.17	0.01
		(0.36)	(0.27)	(0.26)	(0.26)	(0.21)	(0.20)	(0.19)	(0.22)	(0.22)	(0.28)
	MKTRF	1.16***	1.08***	1.10***	1.00***	0.97***	1.00***	0.88***	0.90***	0.96***	1.09***
		(0.06)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.05)
	SMB	0.22**	0.07	0.11*	0.23***	0.12**	0.14***	0.20***	0.18***	0.20***	0.15**
		(0.08)	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	(0.07)
MOM_ac	HML	0.29***	0.04	0.05	0.04	-0.01	0.04	0.05	0.09**	0.15***	0.09
		(0.08)	(0.06)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.06)
	WML	-0.82***	-0.71***	-0.51***	-0.41***	-0.24***	-0.12***	-0.03	0.06	0.21***	0.35***
		(0.06)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.05)
	R-squared	0.89	0.91	0.91	0.89	0.90	0.91	0.89	0.86	0.86	0.81
	Adj. R-squared	0.89	0.91	0.90	0.88	0.90	0.90	0.89	0.86	0.86	0.80
	Intercept	0.44	0.37	0.45	0.07	0.43*	0.44*	0.24	0.27	0.40*	0.18
		(0.27)	(0.26)	(0.28)	(0.23)	(0.24)	(0.23)	(0.22)	(0.20)	(0.21)	(0.26)
	MKTRF	1.05***	1.02***	1.01***	1.13***	1.02***	1.00***	0.93***	0.95***	0.97***	1.06***
		(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.04)
	SMB	0.14**	0.13**	0.17**	0.10*	0.21***	0.23***	0.17***	0.14***	0.23***	0.10
		(0.07)	(0.06)	(0.07)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)
MOM_vol	HML	0.19***	0.06	0.16***	0.07	0.00	0.05	0.08*	0.09**	0.03	0.08
		(0.06)	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.06)
	WML	-0.69***	-0.63***	-0.41***	-0.34***	-0.37***	-0.22***	-0.11***	0.02	0.11***	0.39***
		(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
	R-squared	0.91	0.91	0.88	0.91	0.90	0.89	0.88	0.88	0.88	0.81
	Adj. R-squared	0.91	0.91	0.87	0.91	0.90	0.89	0.88	0.88	0.87	0.81
	Intercept	-0.20	0.38	0.31	0.53*	0.32	0.35*	0.43**	0.13	0.50***	0.56***
		(0.38)	(0.31)	(0.24)	(0.30)	(0.21)	(0.20)	(0.18)	(0.18)	(0.17)	(0.18)
	MKTRF	1.39***	1.28***	1.27***	1.08***	0.97***	0.98***	0.86***	0.90***	0.85***	0.56***
		(0.06)	(0.05)	(0.04)	(0.05)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
	SMB	0.17*	0.20***	0.16***	0.26***	0.17***	0.15***	0.19***	0.18***	0.05	0.07*
		(0.09)	(0.07)	(0.06)	(0.07)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
LOVOL	HML	0.31***	0.24***	0.21***	0.16**	0.10**	-0.06	0.04	-0.06	-0.16***	0.03
		(0.08)	(0.07)	(0.05)	(0.06)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
	WML	-0.63***	-0.33***	-0.23***	-0.32***	-0.26***	-0.21***	-0.16***	-0.06*	-0.09***	0.05
		(0.07)	(0.06)	(0.04)	(0.05)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
	R-squared	0.88	0.89	0.92	0.87	0.90	0.90	0.90	0.90	0.89	0.75
	Adj. R-squared	0.88	0.88	0.92	0.86	0.90	0.90	0.90	0.90	0.89	0.75

Continued on next page

Table 8: Four Factor Regression Summary for Long-only Factor Portfolios: Jan 2007 to Mar 2021

		D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9	D_10
BAB	Intercept	0.25	-0.16	-0.02	0.51**	0.39	0.48**	0.29	0.47**	0.68***	0.54***
		(0.44)	(0.29)	(0.29)	(0.24)	(0.26)	(0.23)	(0.19)	(0.20)	(0.22)	(0.21)
	MKTRF	1.39***	1.23***	1.11***	1.07***	1.02***	1.05***	0.88***	0.86***	0.77***	0.57***
		(0.07)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.04)	(0.03)
	SMB	0.02	0.09	0.11	0.23***	0.18***	0.19***	0.26***	0.19***	0.16***	0.14***
		(0.10)	(0.07)	(0.07)	(0.06)	(0.06)	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)
	HML	0.46***	0.21***	0.29***	0.16***	0.18***	-0.08*	-0.05	-0.12***	-0.08*	-0.03
		(0.09)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)	(0.04)
	WML	-0.64***	-0.40***	-0.25***	-0.23***	-0.16***	-0.20***	-0.15***	-0.16***	-0.10***	0.07*
		(0.08)	(0.05)	(0.05)	(0.04)	(0.05)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)
	R-squared	0.86	0.90	0.87	0.90	0.87	0.89	0.90	0.87	0.82	0.70
	Adj. R-squared	0.85	0.89	0.87	0.90	0.87	0.89	0.90	0.87	0.82	0.70
BETA	Intercept	0.71***	0.56***	0.46**	0.57***	0.42*	0.27	0.11	-0.09	0.38	-0.10
		(0.21)	(0.20)	(0.20)	(0.20)	(0.23)	(0.23)	(0.21)	(0.28)	(0.32)	(0.43)
	MKTRF	0.48***	0.87***	0.89***	0.96***	0.98***	1.04***	1.00***	1.15***	1.23***	1.54***
		(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.05)	(0.05)	(0.07)
	SMB	0.21***	0.13***	0.25***	0.19***	0.19***	0.12**	0.14***	0.21***	0.13*	0.04
		(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)	(0.07)	(0.08)	(0.10)
	HML	0.09**	-0.13***	-0.06	-0.08*	0.01	0.09*	0.19***	0.20***	0.17**	0.35***
		(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)	(0.06)	(0.07)	(0.09)
	WML	0.04	-0.05	-0.12***	-0.21***	-0.16***	-0.14***	-0.24***	-0.30***	-0.48***	-0.57***
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.06)	(0.08)
	R-squared	0.68	0.86	0.88	0.91	0.88	0.88	0.91	0.89	0.88	0.87
	Adj. R-squared	0.68	0.85	0.88	0.90	0.88	0.88	0.91	0.88	0.88	0.86
GROW_mp	Intercept	0.49*	0.86***	0.60**	0.21	0.06	0.09	0.59***	0.33	0.12	0.04
		(0.29)	(0.25)	(0.27)	(0.20)	(0.23)	(0.19)	(0.20)	(0.21)	(0.23)	(0.29)
	MKTRF	1.14***	1.03***	1.06***	0.96***	0.97***	0.93***	0.94***	0.92***	1.04***	1.12***
		(0.05)	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)	(0.05)
	SMB	0.15**	0.14**	0.05	0.14***	0.21***	0.11**	0.16***	0.20***	0.18***	0.34***
		(0.07)	(0.06)	(0.06)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.07)
	HML	0.35***	0.00	-0.03	-0.03	-0.01	0.07*	0.09**	0.11**	0.08*	0.19***
		(0.06)	(0.05)	(0.06)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)	(0.06)
	WML	-0.61***	-0.60***	-0.52***	-0.28***	-0.21***	-0.06	-0.07*	-0.05	0.07*	0.04
		(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)
	R-squared	0.91	0.91	0.89	0.91	0.88	0.90	0.89	0.88	0.87	0.85
	Adj. R-squared	0.91	0.90	0.89	0.91	0.88	0.90	0.89	0.88	0.87	0.85
QUAL	Intercept	-0.27	0.12	0.36	-0.12	0.48**	0.46**	0.69***	0.67***	0.66***	0.48**
		(0.30)	(0.27)	(0.23)	(0.22)	(0.22)	(0.22)	(0.22)	(0.20)	(0.22)	(0.24)
	MKTRF	1.17***	1.10***	1.12***	1.11***	0.95***	0.93***	0.96***	0.83***	0.97***	0.87***
		(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)
	SMB	0.14**	0.06	0.13**	0.12**	0.19***	0.19***	0.14***	0.15***	0.16***	0.19***
		(0.07)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)
	HML	0.35***	0.30***	0.08*	0.11**	0.02	-0.05	-0.16***	-0.09**	-0.07	-0.01
		(0.06)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)
	WML	-0.29***	-0.22***	-0.31***	-0.24***	-0.26***	-0.19***	-0.20***	-0.23***	-0.06	-0.07
		(0.06)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
	R-squared	0.88	0.89	0.91	0.91	0.89	0.88	0.88	0.88	0.87	0.83
	Adj. R-squared	0.88	0.88	0.91	0.91	0.89	0.88	0.88	0.88	0.86	0.83

Standard errors in parentheses under each coefficient.

* p<.1, ** p<.05, ***p<.01

The value factor methodologies have two rather contrasting results using FF4. The winner portfolio with the implementation using Price-to-Book (VAL_ac) shows a significant and positive (0.62***) exposure to HML while the loser portfolio has significant and negative coefficients (-0.16***). For VAL_ac, the HML factor falls below 20% below decile 8. The multi-parameter implementation of value (VAL_mf) has the reverse exposure to HML: the loser portfolio has a significant and positive (0.30***) β to HML, while the winner portfolio has no statistically significant β. VAL_mf does not show exposure to the academic value factor. Both variants seem to be 'Small' cap tilted: HML β is generally positive across all deciles. Both flavours have negative exposure to WML in the higher decile portfolios. This result is consistent with other global research on the relationship between value and momentum (Asness et al., 2013). R-square is lower at the extremes than the middle deciles -

indicating some relationship between our chosen parameters and relative performance. We cannot reject the null hypothesis that $\alpha = 0$ for the winner portfolios for both variants. VAL_ac meets all our criteria for exposure to HML while VAL_mf does not. As we have said before, *not all factor implementations are equal*.

The momentum factor implementations show a difference of degree, but both meet our criteria for factor exposure. For both, the exposure to WML changes from significant and negative to significant and positive between the lowest deciles (-0.82*** for MOM_ac and -0.69*** for MOM_vol respectively) and the highest deciles (0.35*** for MOM_ac and 0.39*** for MOM_vol respectively). WML β falls below 20% below decile 10 for MOM_vol and decile 9 for MOM_ac. Momentum shows short persistence. As we shall see, this has operational implications. Both variations skew towards the smaller market-cap firms in the S&P BSE200 in their respective loser portfolios. HML exposures do not exhibit any statistically robust relationship across deciles. The statistically significant α seen in the CAPM regression for the highest decile portfolio disappears with the FF4 model. The introduction of WML has reduced the α - a robust result showing that the winner portfolios do have momentum.

The rest of our factor strategies do not have a direct academic factors in the IIMA Dataset to examine factor exposure. For these other styles we see how much the FF4 decomposition can explain returns and specific factor exposures. We have two flavours of low volatility: realised volatility (LOVOL), longer-term beta (BAB). The firms in the portfolios are not controlled for size or value. The BAB variation tilts towards smaller market-cap firms in the S&P BSE 200 in the winner portfolios (0.14***). The LOVOL variant is less clear in its relationship with SMB. The winner portfolio has a much less significant SMB β (0.07*). For both variants, loser portfolios have a significant and positive bias towards value companies. With WML both variations show increasing coefficients from loser to winner portfolios. The winner portfolios of both variants have similar α and MKT β with the r-square for LOVOL (0.75) being higher than that of the r-square for BAB (0.70). The FF4 model does not fully account for the returns for the low volatility winner portfolio. To examine persistence, we look at r-squares of the FF4 model. The relatively low r-squares of the winner portfolio increases to about 0.90 by decile 8 and stays elevated for the lower deciles. Both variants show statistically significant αs even in decile 9.

High beta winner portfolio is biased towards value firms (0.35***) and a negative WML β (-0.57***) with no statistically significant α and a reasonably high r-square (0.87). The loser portfolio for BETA is nothing other than the low volatility variant and it is, not surprisingly, similar to the winner portfolios of LOVOL and BAB with a bias towards small-cap, a modest r-square and a significant and positive α. As described, the high beta strategy in itself is unlikely to appeal, but the results reiterate the attractiveness of the low volatility style. The winner portfolios of the multi-parameter growth factor is biased towards small cap (0.34***) and value (0.19***) with no statistically significant α and a reasonably high r-square (0.85). Across the deciles, no clear pattern of the SMB and HML is apparent, though r-square drops from the loser decile to the winner decile. The WML parameter is more evident is the lower deciles than the upper deciles. α is statistically significant for the loser (and deciles 2 and 3). This is likely a case of 'correlation but not causation'. Adopting the r-square metric for persistence, by decile 6, the r-square is close to 90%.

Finally, quality. Other than low volatility, quality is the only other factor winner portfolio with a positive and significant alpha (0.48**). Deciles 5 upward show statistically significant positive α. Other than a bias to small-cap firms, and a negative exposure to WML, there is little information to be gleaned from the FF4 regressions. The factor style is also one of the most persistent : both in terms of r-squares and statistical evidence of α. It is only in deciles 4 and 5 that there seems to be a turn for the worse. Quality firms command higher valuations (negative HML β than firms in the lower deciles: the strength is modest but statistically significant. In terms of persistence, r-square is 88% from decile 8 and α significance drops to 5% from decile 7. We take decile 8 as a cut-off.

For size, value and momentum, Table 9 summarises the FER. Except for the multi-parameter value variant, all the other winner portfolios show a positive exposure to the underlying factor. Size and VAL_ac have significantly higher exposures to MKT, followed by momentum. Stripping away MKT, the momentum variants demonstrate strong exposure to the WML factor, with MOM_vol showing the largest FER and is the most "factor-efficient" portfolio. VAL_ac and size also show the factor exposure. VAL_mp, on the other hand, takes on more non-target factor exposure, despite being classified as value. Once again, *not all factor implementations are the same.*

Table 9: Factor exposures, total absolute non-target exposures (with and without MKT) and FER (with and without MKT): Jan 2007 to Oct 2021

	MKTRF	SMB	HML	WML	Non Target	FER	Non Target ex MKT	FER ex MKT
SIZE	1.20	0.41	0.22	-0.55	1.97	0.21	0.77	0.53
VAL_ac	1.19	0.12	0.62	-0.43	1.74	0.36	0.55	1.13
VAL_mp	1.01	0.19	-0.04	-0.22	1.50	-0.03	0.49	-0.08
MOM_ac	1.09	0.15	0.09	0.35	1.33	0.26	0.24	1.46
MOM_vol	1.06	0.10	0.08	0.39	1.24	0.31	0.18	2.17

This table shows the summary of factor exposure (the β from the FF4 regression) for the winner portfolio. FER is calculated including and excluding MKT. Long-only portfolios inherently have MKT exposure.

The FF4 regressions results show:

- Long-only factor winner portfolios for size, value, momentum show clear evidence of factor exposure.
- Quality and low volatility winner portfolios show positive and statistically significant α in our sample.
- Not all factor styles are equal. Two variants that are similarly categorised can lead to diverging outcomes. Having multiple parameters is no guarantee of increased exposure to factors. There will be differences in outcomes based upon the factor measurement and strategy implementation[34]
- Empirical tests can uncover persistence of factor exposures.
- It is critical to ensure the factor exposure is tested empirically. This requires having credible and independent datasets which are easily accessible to allow for comprehensive and robust testing.

[34]look-back periods, portfolio holding periods, portfolio weight strategies amongst a host of operational parameters which are essential in translation a theoretical strategy into the real world.

Agarwalla et al. (2013) demonstrated evidence for traditional academic factors in the Indian equity market. Systematic factor portfolios using the largest and most liquid stocks in India also exhibit statistically robust evidence of factor exposure. The significant β for size, value and momentum of our winner portfolios using over 10 years of data demonstrates this. Moving beyond size, value and momentum, there are other anomalies which the FF4 is unable to fully explain, which should encourage researchers and managers hunting for the anomalies to exploit.

4.5 Long-only Systematic Winner Portfolios: Persistence

After showing that long-only factor portfolios demonstrate robust evidence of factor exposure, we evaluate whether these winner portfolios show persistence of factor exposure. Specifically, do the firms selected in the top decile remain in the top decile over time? We construct decile portfolios on a monthly basis. Variables like price change monthly, while some of the accounting variables are refreshed annually. This will be reflected in factor scores changes for each firm at varying rates over time. By construction, at $t = t{+}0$ the score of all the constituents in the winner portfolio is 10. Over time, as the constituents scores change and they move deciles, the average score of the winner portfolio changes. We compute the changes of score over time for all the winner portfolios during our observation period. From our FF4 analysis, for each factor style we identity a decile portfolio below which the factor style dissipates. From $t{=}t{+}1$, the original winner portfolio diverges from the most current winner portfolio as the scores of the individual firms change. As a result, the performance of the original portfolio moves down from a decile 10 portfolio. When the portfolio score reaches the cut-off, it no longer can be expected to deliver what the most current winner portfolio delivers.

Table 10: Winner Portfolio Factor Persistence Over Time: Jan 2007 to Oct 2021

Time	SIZE	VAL_ac	VAL_mp	MOM_ac	MOM_vol	LOVOL	BAB	BETA	GROW_mp	QUAL
t	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0
t+1	9.3	9.6	9.7	9.5	9.5	9.8	9.8	9.7	9.4	9.8
t+2	8.6	9.3	9.3	9.0	9.0	9.6	9.6	9.5	8.8	9.6
t+3	8.0	8.9	9.0	8.5	8.5	9.4	9.4	9.2	8.3	9.4
t+4	7.4	8.6	8.7	8.0	8.1	9.2	9.2	9.0	7.7	9.2
t+5	6.7	8.3	8.4	7.5	7.6	9.0	8.9	8.7	7.2	9.0
t+6	6.1	7.9	8.1	7.0	7.2	8.8	8.7	8.5	6.6	8.8
t+7	5.9	7.9	8.0	6.7	6.9	8.7	8.7	8.3	6.3	8.7
t+8	5.6	7.8	7.9	6.3	6.6	8.6	8.6	8.2	6.0	8.6
t+9	5.4	7.7	7.7	5.9	6.4	8.5	8.6	8.1	5.6	8.5
t+10	5.2	7.6	7.6	5.6	6.1	8.4	8.5	8.0	5.3	8.4
t+11	5.0	7.5	7.5	5.2	5.9	8.3	8.4	7.8	5.0	8.4
t+12	4.9	7.5	7.4	5.1	5.6	8.2	8.4	7.7	4.8	8.3
t+24	3.1	5.9	5.9	5.0	5.3	7.6	7.7	6.3	4.5	7.3
t+36	2.5	5.0	5.5	4.5	4.9	7.5	7.5	5.5	4.1	6.9

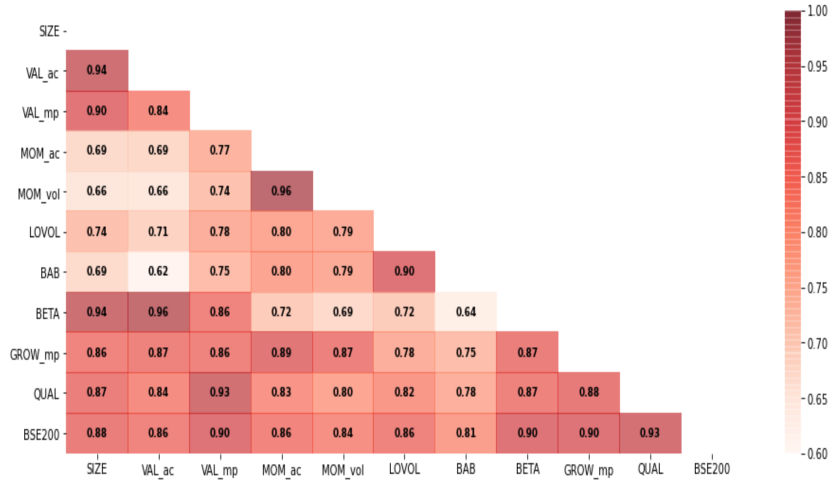
This table shows mean score over time for the constituents in D_10 portfolio for each factor. We compute the decile of each firm in the D_10 portfolio over $t = t{+}1, t{+}2, t{+}3..t{+}12, t{+}24$ and $t{+}36$ months and calculate the average across the cohort. For firms that are no longer part of the S&P BSE 200 index constituents, we assign a score of 0.

Table 10 summarises the persistence of the winner portfolios across the different factor styles. Table 10 should be along with Table 8. GROW_mp dissipates most quickly in our analysis. This information needs to looked along with factor exposures dissipation analysis from FF4. We had decile 6 as the factor-dissipation cut-off and the table shows this is reached by $t{+}8$. Momentum portfolios also dissipate relatively quickly (also see Jegadeesh and Titman (1993); Raju and Chandrasekaran (2019)). The cut-off from the FF4 analysis of Decile 9 is reached by t+3. The cut-off for size (decile 5 reached at t+11), VAL_ac (decile 8 reached at t+6), low volatility (decile 8 reached at t+12) and quality (decile 8 reached at t+12). We have seen that momentum, low volatility and quality are attractive from a risk-adjusted-return perspective. Of these, the last two are persistent for longer periods.

All factors dissipate over time. The analysis of persistence and connecting it to the performance of decile portfolios using tools such as the FF4 regression shows a framework using empirical evidence to review operational matters like holding periods of portfolios before the factor-style dissipate completely.

4.6 Long-only Systematic Winner Portfolios: Correlations

Figure 3: Correlation of excess returns of winner portfolios and S&P BSE 200: Jan 2007 to Oct 2021



Source: Authors calculations, Refinitiv. All returns are excess to risk free returns.

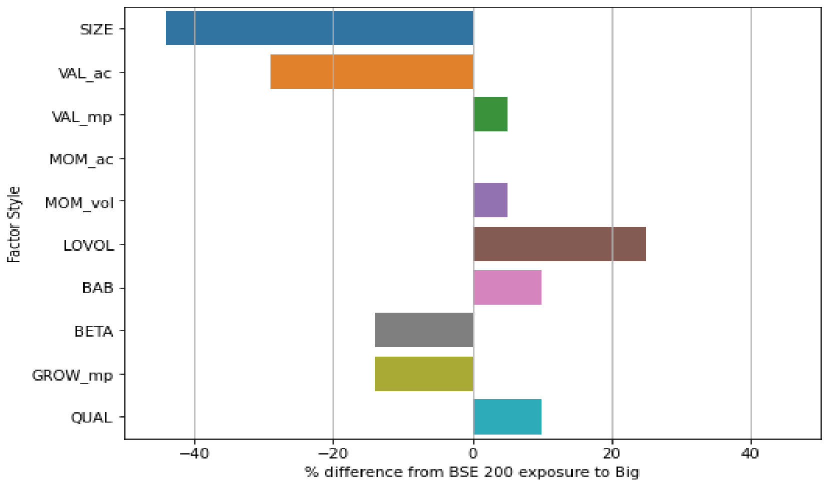
Academic long-short factors have low correlation between each other (see Agarwalla et al. (2013) for evidence in India). We have already seen that MKT β is significant in both the one factor and FF4 regressions. Therefore, we would expect long-only factor-strategy portfolios to have significantly higher correlations between each other. Figure 3 summarises the correlations between the excess returns of our winner portfolios. This result should be an important consideration for portfolio construction using long-only factor portfolios.

Styles like low volatility, momentum, quality and growth show lower correlations with other styles. Amongst flavours of factors, momentum has the higher correlation between the two versions, followed by low volatility and value has the weakest correlation between the two versions in this study. Once again, the FF4 regressions in Table 8 shine more light on the underlying reasons why. The relatively high correlations between the two momentum variations, for example, also brings up an important point. Marketing materials of factor-strategy funds tend to gloss over the underlying market exposure. Two variations under the same factor style could offer very little in the way of diversification. investors should examine whether factor-style tracking funds herd together. The analysis of correlations gives us a quick and useful guide into how factors could be combined together to form multi-factor portfolios.

4.7 Size bias in Long-Only Factor Winner Portfolios

To examine the size bias of the winner portfolios, we plot the difference in the median sizes of firms in the monthly winner portfolios for each style and median size of firms in the S&P BSE 200 (Table 2). Figure 4 shows the results. The SIZE winner portfolio only has 'small' firms and shows a negative difference equal to the median exposure of the S&P BSE 200 constituents to Big. VAL_ac, BETA and GROW_mp portfolios have a bias towards Small firms. All the other portfolios are over-weight the Big firms. LOVOL is the most overweight Big[35]

Figure 4: Summarised Size Deviation of Factor Winner Portfolios From S&P BSE 200 : Jan 2007 to Oct 2021



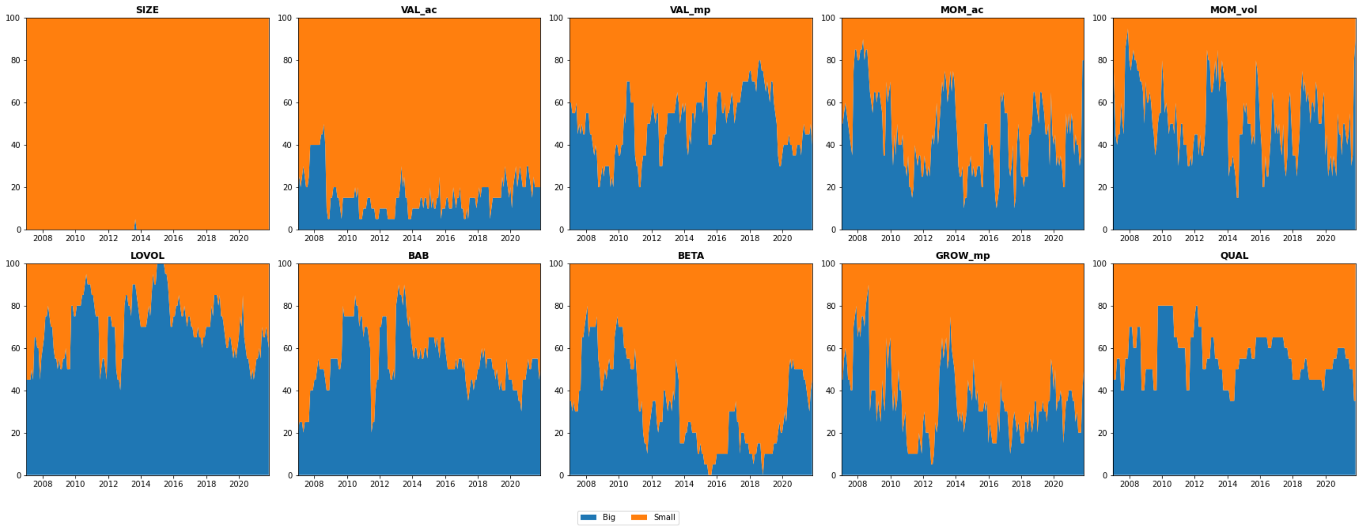
Source: Authors calculations, Refinitiv.
The bars show the difference in the median number of firms in the portfolio by their size characteristic over the entire period from the median number of firms in the S&P BSE 200 constituents categorised as 'Big'. Negative values imply that the portfolio has a larger percentage of 'Small' companies and positive values imply the portfolio has a larger bias to 'Big' firms than the index.

The medians, like any average, reduce the underlying changes. Figure 5 shows the winner portfolios every month broken down by the size breakpoints determined annually. For each portfolio, there is variation around a broad trend described by the median. LOVOL has the bias towards Big, but also has a significant amount of variation across the months. Both versions of momentum also show similar exposure to size. The value variations are very different in their size exposure with VAL_ac taking a much larger exposure to Small over the period. As we saw in the correlation analysis, the variations of value have two very different characteristics in size exposure.

The variation to size highlights, again, the importance of empirically examining the portfolio characteristics across various dimensions to fully understand the nature of risks that empirical based methodologies carry with them.

[35] In Table 8 LOVOL does not have a negative SMB β. This difference arises due to the two very different classifications between the Data Library for the Indian Market and our approach.

Figure 5: Factor Winner Portfolios by Size: Jan 2007 to Oct 2021



Source: Authors calculations, Refinitiv.
The charts show the winner factor portfolio constituents split by size (Big or Small) using the size breakpoints determined annually in September

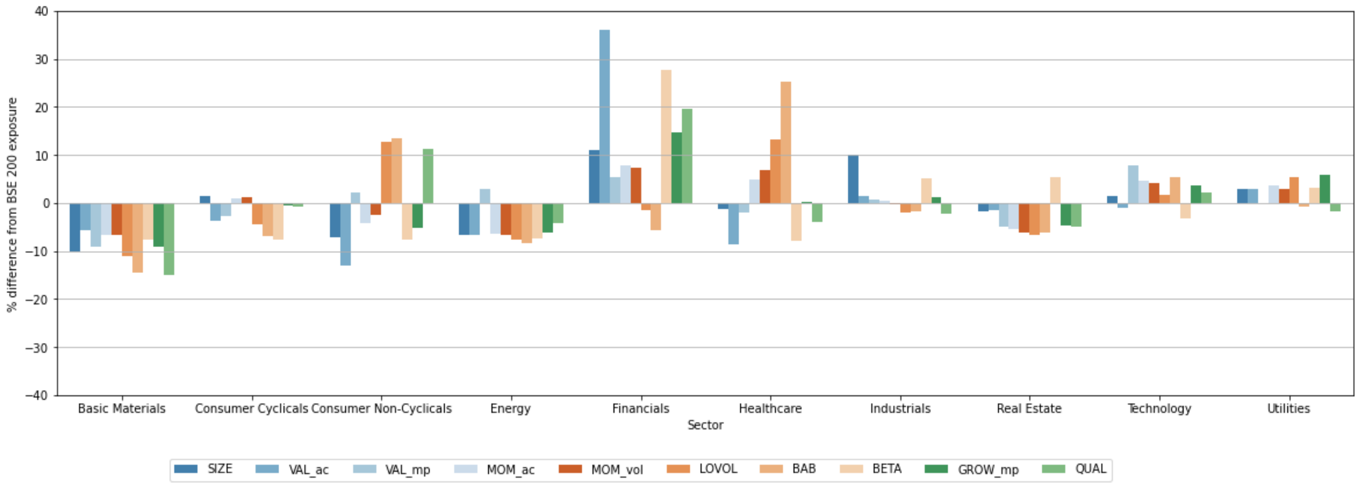
4.8 Sector bias in Long-Only Factor Winner Portfolios

For sectoral allocation of winner portfolios, we follow a similar procedure used for Size exposure. For each winner portfolio we compute the median sector allocation of all constituent firms across the period and compare it to the median sector allocations of the constituents of the S&P BSE 200 index for the same period. Figure 6 shows the differences for each factor winner portfolio. All the portfolios are underweight Basic Materials. Energy and Real Estate are almost universally under-weighted. While there is no sector which is over-weighted by all factor winners, Financial and Healthcare, Technology and Utilities are overweight in a majority of the strategies we have considered. In particular, the overweight to Financial and Healthcare is significant. The median sectoral weights give insight into the sectoral 'preference' of factors. Quality and low volatility have over weights to Consumer Non-Cyclicals. Value has a significant over weight to financials[36]. Momentum finds favour in Financials, Healthcare, Technology and Utilities. Quality overweights Financials, Consumer Non-Cyclicals and Financials.

Figure 7 shows the changes in sectoral allocation across the winner portfolios over time. Like we have seen for Size, the allocations are dynamic. This dynamic allocation provides opportunities for asset managers and investors to use factors in constructing portfolios with specific objectives in mind. Extending the returns-based analysis, we note size and sectoral preferences by the various long-only factor winner portfolios we have analysed. Adviser and investors looking to add factor exposures to their portfolios are well advised to adopt a similar approach to optimise the diversification benefits of portfolios. The S&P BSE 200 constituents form the mainstay of many existing portfolios and adding exposure from factor strategy portfolios constructed from the same constituents might add less diversification than naive expectations.

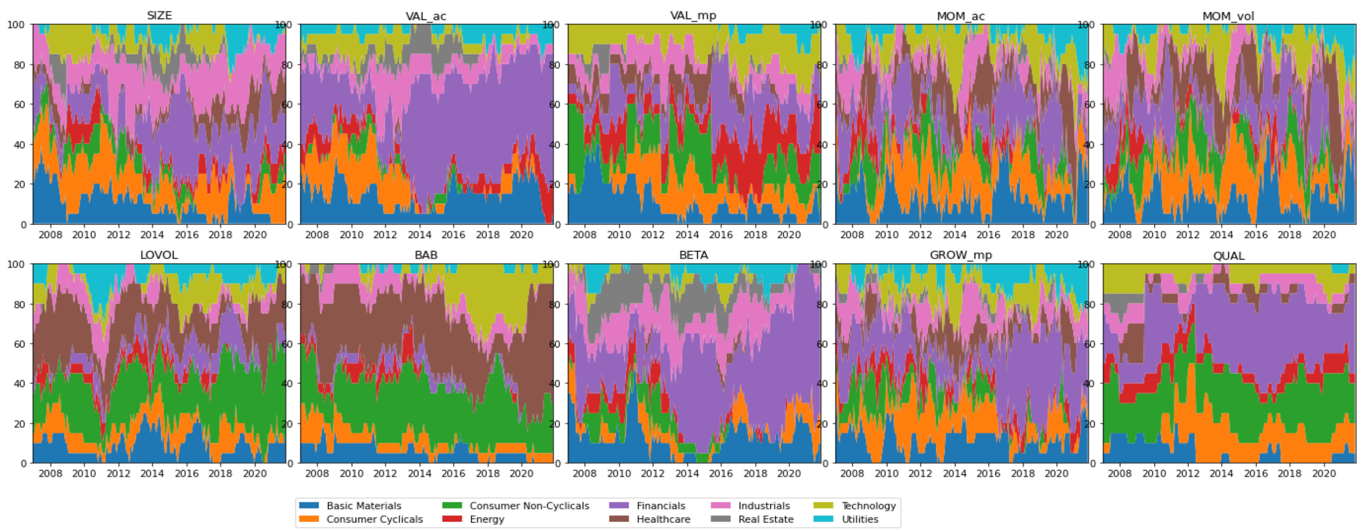
[36]The naive Price-to-Book metric is likely causing this sectoral weighting. A different value metric will likely have a different sector exposure.

Figure 6: Summarised Sector Deviation of Factor Winner Portfolios From S&P BSE 200 : Jan 2007 to Oct 2021



Source: Authors calculations, Refinitiv.
The bars show the difference in median sector exposure of firms in the winner portfolio over the entire period from the median sector exposure of firms in the S&P BSE 200 constituents. Negative values imply that the portfolio has a an under-weight position in the sector and positive values imply an over-weight bias to the sector breakdown of the index.

Figure 7: Factor Winner Portfolios by Sector: Jan 2007 to Oct 2021



Source: Authors calculations, Refinitiv.
The charts show the winner factor portfolio constituents split by sector of constituent firms

4.9 Long-only Systematic Winner Portfolios: Horserace

To examine if a particular set of factors is a consistent winner we look at an annual calendar returns horserace. Figure 8 shows the outcome of such a horserace computed on a calendar year basis with the winner factor portfolios. These results are aligned to similar factor and factor tilt portfolio horserace results in various other markets. Momentum[37], low volatility[38] and quality would rank order higher than the broad S&P BSE 200 Index over the various years. But this naive rank ordering ignores the very real volatility in returns across all the winner portfolios. For example, globally, value, in particular, has underperformed the broad market for

[37] MOM_vol ranks ahead of MOM_ac
[38] BAB ranks ahead of LOVOL

Figure 8: Horserace heatmap: 2007 to 2021

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
BSE200	7	3	7	5	8	9	3	9	8	4	8	3	3	6	7
SIZE	5	7	5	10	9	1	11	5	9	3	5	8	9	5	6
VAL_ac	4	5	4	9	10	7	9	10	11	5	3	10	11	10	3
VAL_mp	10	8	2	7	6	8	7	2	6	1	10	7	7	7	8
MOM_ac	3	9	9	8	3	5	5	4	5	9	2	6	2	4	4
MOM_vol	2	6	11	1	2	6	4	1	1	6	6	5	4	1	2
LOVOL	9	1	8	3	4	11	1	6	4	8	11	2	5	2	9
BAB	8	2	10	2	1	10	2	7	2	10	9	1	1	3	11
BETA	6	11	3	11	11	2	10	11	10	11	1	9	10	11	5
GROW_mp	1	10	6	6	7	4	8	8	3	7	4	11	8	8	1
QUAL	11	4	1	4	5	3	6	3	7	2	7	4	6	9	10

Source: Authors calculations, Refinitiv.
This chart shows ranks of each factor style winner portfolios and the S&P BSE 200 index ranked by annual returns for the calendar year. For 2021, the returns are ranked based on Dec 2020 through Oct 2021.

almost two decades but that does not imply that the factor is no longer relevant[39].

The takeaway from the horserace is that while winner momentum, low volatility and quality winner factor portfolios demonstrate out-performance across our observation period, no single factor in our sample has performed better than all other winner portfolios all the time. There is an ongoing debate on factor rotation in other markets. In the Indian context, factor rotation is a possible avenue for future empirical research.

4.10 Long-only Systematic Winner Portfolios: Turnover and Estimated Shrinkage of Alpha

Having dealt with the research objectives without accounting for implementation costs, we finally turn to estimating shrinkage of returns on implementation. Implementation costs are largely brokerage and impact costs. The former is a function of turnover and the latter to the trading in 'Small' size firms. First, we turn to turnover. High turnover is seen as one of the primary drivers of shrinkage of theoretical returns. As we have noted, our approach[40], by definition, will likely have higher turnover than most actual implementations (see for instance Ross et al. (2017)).

The number of constituent changes every month is a useful starting point for the turnover. Factor styles with low persistence will have higher turnover of constituents. Table 11 summarises the annual turnover in number of constituents and percentage across all the factor styles we consider. Momentum with low persistence has the most number of constituent changes - almost a third of the constituents change every month. On the other hand, quality, a persistent factor, shows the fewest changes in constituents. BAB also shows lower

[39]See `https://www.aqr.com/Insights/Perspectives/A-Gut-Punch` for an excellent self-reflection by AQR's Cliff Asness on the challenges of Value.

[40]Monthly-rebalanced, EW with no optimisation or buffers to reduce turnover.

Table 11: Constituents Turnover in Long Only Winner Factor Portfolios: 2007 to 2021

	SIZE		VAL_ac		VAL_mp		MOM_ac		MOM_vol		LOVOL		BAB		BETA		GROW_mp		QUAL	
	Num	Pct	Num	Pct	Num	Pct	Num	Pct	Num	Pct	Num	Pct	Num	Pct	Num	Pct	Num	Pct	Num	Pct
2007-12-31	4.3	21.5	2.3	11.5	2.2	11.0	5.3	26.5	6.3	31.5	3.1	15.5	1.7	8.5	2.7	13.5	5.0	25.0	1.4	7.0
2008-12-31	3.3	16.5	3.2	16.0	2.5	12.5	5.7	28.5	5.9	29.5	2.1	10.5	2.0	10.0	2.4	12.0	5.0	25.0	1.2	6.0
2009-12-31	1.6	8.0	2.5	12.5	1.7	8.5	7.0	35.0	6.2	31.0	1.4	7.0	0.9	4.5	1.5	7.5	6.1	30.5	1.1	5.5
2010-12-31	3.2	16.0	2.2	11.0	3.2	16.0	6.7	33.5	7.1	35.5	2.3	11.5	1.2	6.0	2.8	14.0	6.6	33.0	1.1	5.5
2011-12-31	4.8	24.0	3.8	19.0	2.6	13.0	6.1	30.5	6.5	32.5	3.2	16.0	2.9	14.5	3.7	18.5	4.9	24.5	2.2	11.0
2012-12-31	4.8	24.0	4.4	22.0	3.3	16.5	7.2	36.0	6.9	34.5	2.4	12.0	2.6	13.0	2.4	12.0	6.1	30.5	1.9	9.5
2013-12-31	3.6	18.0	3.4	17.0	2.1	10.5	6.2	31.0	6.6	33.0	3.1	15.5	2.4	12.0	2.6	13.0	5.6	28.0	1.2	6.0
2014-12-31	2.5	12.5	1.2	6.0	1.8	9.0	5.5	27.5	6.4	32.0	2.9	14.5	1.9	9.5	1.2	6.0	4.9	24.5	0.8	4.0
2015-12-31	2.8	14.0	2.0	10.0	3.1	15.5	5.2	26.0	6.7	33.5	2.5	12.5	1.5	7.5	2.2	11.0	5.1	25.5	0.4	2.0
2016-12-31	2.5	12.5	2.0	10.0	2.9	14.5	5.6	28.0	6.8	34.0	1.8	9.0	1.2	6.0	2.5	12.5	4.8	24.0	0.8	4.0
2017-12-31	2.2	11.0	1.4	7.0	2.9	14.5	6.4	32.0	5.6	28.0	2.2	11.0	1.8	9.0	2.9	14.5	5.2	26.0	1.2	6.0
2018-12-31	3.8	19.0	1.8	9.0	2.0	10.0	4.8	24.0	6.8	34.0	2.1	10.5	1.3	6.5	2.0	10.0	3.5	17.5	0.8	4.0
2019-12-31	2.9	14.5	1.7	8.5	2.1	10.5	6.0	30.0	7.6	38.0	2.2	11.0	1.7	8.5	1.9	9.5	5.3	26.5	1.0	5.0
2020-12-31	3.5	17.5	2.5	12.5	1.5	7.5	5.5	27.5	6.0	30.0	3.2	16.0	1.8	9.0	2.2	11.0	5.4	27.0	0.7	3.5
2021-10-31	2.8	14.0	1.7	8.5	2.3	11.5	6.0	30.0	6.8	34.0	1.8	9.0	1.2	6.0	1.8	9.0	3.7	18.5	0.8	4.0

This table shows the mean number of monthly constituent changes in winner portfolios as well as the proportion of the total number of constituents as of December every year for the prior twelve months expressed as a percentage. For 2021, the calculation ends on October 2021.

constituent changes every month. Using this table, it is quite trivial to estimate the brokerage costs associated with the new constituents for winner long-only factor portfolios. For instance, assuming a 20 bps brokerage commission for each leg, for MOM_vol with around 6.5 changes a month, the annual brokerage drag would be about 1.6%[41], while for the quality portfolio with, on average 1.1 constituent changes per month, it would be about 30 basis points. Table 12 summarises the annual turnover computed on a calendar year basis using the definition turnover outlined in Section 3. We show $turnover_{rebalancing}$, $turnover_{new}$ and $turnover_{total}$ from equation 8.

Table 12: Annualised Turnover of Winner Factor Portfolios: 2007 to 2021

	SIZE			VAL_ac			VAL_mp			MOM_ac			MOM_vol		
	Reb	New	Total	Reb	New	Total	Reb	New	Total	Reb	New	Total	Reb	New	Total
2007-12-31	50	300	340	40	150	190	40	150	190	40	310	360	30	360	400
2008-12-31	50	170	230	40	180	230	50	140	190	40	320	360	40	350	400
2009-12-31	50	90	140	40	150	190	50	100	160	30	430	460	30	380	410
2010-12-31	30	200	230	30	140	170	30	200	220	20	400	420	20	420	440
2011-12-31	40	280	320	40	210	250	30	150	190	30	360	390	20	390	410
2012-12-31	40	290	330	40	260	300	30	210	240	30	440	470	20	420	440
2013-12-31	50	210	250	40	200	240	40	120	160	30	380	410	30	390	430
2014-12-31	40	150	200	40	70	110	40	100	140	30	330	360	30	380	410
2015-12-31	40	160	210	40	120	160	30	180	220	30	310	340	20	400	420
2016-12-31	40	150	190	30	120	160	30	170	210	30	340	360	20	400	430
2017-12-31	30	140	180	40	90	130	30	170	200	20	380	410	20	330	360
2018-12-31	40	210	250	40	100	140	30	120	150	30	280	320	30	410	430
2019-12-31	50	170	220	50	90	150	40	120	160	20	360	390	20	450	470
2020-12-31	40	210	260	40	150	190	40	90	130	30	330	370	30	370	400
2021-10-31	40	170	210	40	100	130	30	140	170	40	350	400	40	390	440

	LOVOL			BAB			BETA			GROW_mp			QUAL		
	Reb	New	Total	Reb	New	Total	Reb	New	Total	Reb	New	Total	Reb	New	Total
2007-12-31	30	200	230	40	110	140	40	160	210	40	320	380	40	90	130
2008-12-31	40	130	160	50	120	170	50	170	220	50	280	330	50	60	120
2009-12-31	30	80	120	30	50	90	40	80	120	40	380	420	50	70	120
2010-12-31	20	140	160	20	70	100	30	170	200	30	400	420	30	60	100
2011-12-31	20	190	220	20	180	200	40	220	260	30	290	320	30	130	160
2012-12-31	20	150	170	20	160	180	40	150	190	30	370	400	30	120	160
2013-12-31	20	190	210	20	140	170	40	160	200	30	340	380	40	70	110
2014-12-31	30	180	210	30	120	150	40	70	110	40	290	330	40	50	90
2015-12-31	20	150	170	20	90	120	40	130	170	40	300	340	30	20	60
2016-12-31	20	110	130	20	70	90	40	150	190	30	300	330	30	50	80
2017-12-31	20	130	150	30	110	130	40	180	220	30	310	340	30	70	100
2018-12-31	20	120	150	30	80	110	40	120	160	40	210	250	30	50	80
2019-12-31	20	130	160	30	100	130	50	110	160	30	320	350	40	60	100
2020-12-31	30	190	220	30	110	140	40	110	150	30	320	360	40	40	80
2021-10-31	30	110	140	30	70	100	40	120	160	50	210	270	30	50	80

This table shows the calculated $turnover_{rebalancing}$, $turnover_{new}$ and $turnover_{total}$ of the equal-weighted winner factor portfolios as of December every year for the prior twelve months expressed as a percentage. For 2021, the calculation ends on October 2021.The numbers are rounded to nearest 10.

As expected, momentum winner portfolios show the highest $turnover_{total}$ - almost turning over once every quarter. The average 6.5 constituent changes per month for MOM_vol in Table 11 translates into a close to 400% turnover. MOM_vol, which uses the higher frequency 6-month measure as one of its components, has a higher turnover than MOM_ac, which uses a longer frequency 12-month measure. $turnover_{new}$ drives a majority of $turnover_{total}$ - not just for momentum, but for all factors. Size, too, has a high $turnover_{total}$ driven by the change in market-cap amongst the smallest firms by market-cap in the S&P BSE 200. QUAL, LOVOL and BAB have relatively lower $turnover_{total}$.

The turnover arising from rebalancing of the equal weighted portfolio is a much smaller contributor to $turnover_{total}$. Most of the turnover costs arise from changes to constituents in our approach. Other weighting schemes will have markedly different turnover rates. Many factor-strategies use longer holding periods and buffers as a means to control turnover. In addition, their weighting schemes are signal-weighted-capital-scaled. While these measures reduce turnover, they will obviously would impact factor-exposure as well as persistence.

[41] 6.5 trades ÷ 20 stock portfolio × 2 legs × 12 months × 20bps

The framework we have developed in this paper can be applied to evaluate these implementation decisions as well.

The second driver of costs is impact costs : the slippage in traded price due to the demand and supply of stocks during trading hours. we can add the impact costs, arising from liquidity based on size. For instance, for the size winner portfolio, has an average change in constituents of 3.2 stocks per month. All of these are is small cap firms. Assuming an average impact cost of 30 bps per trade, we would compute impact costs to be approximately 1.2%[42].

To compute the total costs, we add the costs of brokerage and impact for the monthly rebalancing of portfolios back to equal weights. We follow a similar process used in the computation of these costs for changes to constituents except we only compute single-leg costs and multiply these by the average rebalancing turnover for the style.

Table 13 shows the shrinkage of the average 3-year alphas using our estimates of brokerage and impact costs. While the alpha shrinks due to the costs, winner portfolios from momentum, low volatility, and quality, as defined in this paper, all continue to show positive mean 3-year rolling alphas in excess of the S&P BSE 200 returns. Brokerage costs could add upto 2.0% and impact costs upto 2.4% for our 20 stock portfolio with no optimisation to reduce costs and turnover. For high turnover strategies like momentum and beta, the shrinkage is between 3 and 4% per annum. For 'Small'-cap-heavy strategies[43], the impact cost shrinks the alpha between 1.2-2.4% pa. Low turnover strategies[44] do not suffer significantly due to implementation costs.

Table 13: Estimated Alpha Shrinkage of Winner Factor Portfolios including transaction costs

	Ex-costs 3 yr Alpha	Brokerage	Impact	Total Costs ex Tax	Inc Costs 3 yr Alpha
SIZE	-3.7	1.6	2.4	4.0	-7.7
VAL_ac	-9.6	1.4	1.8	3.3	-12.9
VAL_mp	0.4	1.3	1.2	2.5	-2.1
MOM_ac	6.5	1.9	1.8	3.7	2.7
MOM_vol	9.4	2.0	1.7	3.7	5.6
LOVOL	7.7	1.1	0.7	1.8	5.9
BAB	8.5	1.0	0.8	1.9	6.7
BETA	-13.9	1.4	1.6	3.0	-17.0
GROW_mp	-0.8	1.9	2.1	4.0	-4.7
QUAL	7.1	1.1	0.9	2.0	5.2

This table shows the mean rolling 3 year alphas shown in Table 5, estimated brokerage and impact costs, and alpha after deducting these costs. We assume brokerage costs of 20 bps for each leg. For impact costs, we estimate 5 bps for firms categorised as 'Big' and 30 bps for firms categorised as 'Small'. Brokerage costs are estimated from mean constituent turnover in Table 11. Impact cost estimates use the average size exposure of the long-only winner factor portfolios in Figure 5.

Our results are similar to many studies : momentum strategies having high turnover show a non-trivial shrinkage of theoretical alphas, while low volatility and quality with lower turnover show a fairly small shrinkage. In the Indian context, while some long only factor strategies as we have constructed them show negative alpha,

[42] 3.2 trades per month ÷ 20 stock portfolio × 2 legs × 12 months ×30 bps.
[43] Size, momentum, value
[44] Quality, low volatility

momentum, low volatility, and quality show healthy alphas to the broader market nett of key transaction costs. In these cases, *going 'long' factors is not 'short' change.*

5 Conclusion

Building factor-style equal-weighted winner portfolios from the S&P BSE 200, the most liquid segment of the Indian equity market, we show evidence of factor exposure for size, value and momentum factors. While academic factors for low volatility and quality are not available in India, we show that winner portfolios for these two 'factors' show statistically significant α against both the one-factor and FF4 models. Factor-style implementations of momentum, low-volatility and quality show robust evidence of α relative to the S&P BSE 200. Winner portfolios of size, value, high beta and to a lesser extent growth did not show out-performance for the observation period and implementation we chose. Factor exposures persist over time. Different strategies have different persistence trajectories. As expected, there is significant exposure to the market which makes the correlations between long-only factor strategies higher than the theoretical long-short factor indicates.

The study sheds new light by estimating post-implementation-cost alphas as previous studies have not included costs. Despite our conservative estimates of costs, alpha remains positive after accounting for brokerage and impact costs for momentum, low volatility, and quality implementations. We are confident that real-world implementations, with more sophisticated trading algorithms, will generate positive expected alphas over the long term. We include alternative calculation methodologies for some factors to show that not all implementations of factor strategies are the same. The study also shows size and sector biases in the strategies that are important considerations for diversification benefits when evaluating factor strategy implementations. Factors are not a panacea or a silver bullet for investors. Factors work over long periods. Importantly, they do not work all the time. Investors with shorter time horizons tend to abandon strategies out of favour and switch to those in favour. Using an annual calendar returns horserace, we show that while there is no one consistent winner, momentum, low volatility, and quality rank higher than the broad S&P BSE 200 index over the period under consideration.

As factor models are empirical asset pricing models, the availability of cheap and powerful computing power and access to data sources may result in false positives. Therefore, a blend of economic intuition, behavioural finance insights, and quantitative robustness is imperative to ensure that implemented models do not end up in the "factor zoo" graveyard. The framework outlined in this study can be used to evaluate factor-strategy implementations and make important operational decisions to translate theoretical factor models to the real world.

A logical extension of our study would be to explore factor rotation, multi-factor portfolio combinations and tactical management of single-factor portfolios by looking at factor behaviour over business and economic cycles. This study can be extended to broaden the universe from the top 200 firms by market capitalisation. The small-cap firms tend to show high theoretical alpha but come with higher implementation costs.

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