The Conservative Formula: Evidence from India

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ABSTRACT

We implement the Conservative Formula as outlined in Van Vliet and Blitz (2018) on data from Indian stock markets. It selects 100 liquid stocks based on three criteria: low realised volatility, high net payout yield and strong price momentum. We demonstrate that this simple yet robust formula exposes investors to key factors like low volatility, quality (through operating profitability and investment factors) and momentum in India. The quarterly rebalanced portfolio of 100 stocks significantly outperforms the S&P BSE 100 in absolute returns (by 12.6% pa compound) and risk-adjusted returns. We show the Conservative portfolio's performance outperforms the S&P BSE 100 and the Speculative portfolio over different business cycles. The formula has been shown to work over long periods: in US markets since 1929 and in other markets like Europe, Japan and Emerging Markets. Our paper extends this evidence to India. The conservative formula uses three simple criteria that do not require accounting data and, therefore, should appeal to a broad base of asset owners and managers in India.

Keywords— Factors, Factor Investing, Conservative Formula, India

JEL Classification Codes G11, G12, G15

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1 Introduction

The increasing interest and participation in the equity markets in recent years in India have benefited from tailwinds like the growth of low-cost broking platforms, cheap (or free) online access to structured financial data and affordable computing power. Articles and books which present simple investment formulas are very popular amongst the new generation of equity investors in India. Online stock screeners like the 'Piotroski Scan' (modelled after Piotroski (2000)) and the 'Magic Formula' (based on Greenblatt and Tobias (2005)) are very popular. Books such as "*The Intelligent Investor*" by Graham, "*Coffee Can Investing: The Low Risk Road to Stupendous Wealth*" by Mukherjea et al., "*How to Avoid Loss and Earn Consistently in the Stock Market: An Easy-To-Understand and Practical Guide for Every Investor*" by Paul rank highly in the list of top financial books in India. The easy-to-understand investment formulas presented in engaging stories resonate strongly with investors. These approaches are particularly interesting to the growing Do-it-Yourself investors who prefer to build their variants of these formulaic investing processes. In '*High Returns from Low Risk: A Remarkable Stock Market Paradox'* Van Vliet and Koning present a new investment formula which selects 100 stocks based on volatility, net payout yield and momentum. The paper replicates this 'Conservative Formula' within the Indian equity markets.

The low-volatility anomaly (where returns are not linearly related to risk as measured by volatility) is at the core of the Conservative Formula. In addition, it derives from the academic factor theory, which grew, amongst others, from the seminal work by Fama and French (1993). Factors underlying assets determine asset risk premiums. Risk is not a property of an asset in isolation but instead how assets move about each other. Factors are a premium for enduring bad times. The factor theory of investing specifies different types of underlying factor risk, where each factor represents a different set of bad times. Academics tend to use a parsimonious and persistent group of factors - generally the Fama-French three-factor variant or the five-factor variant (see Fama and French (2015) and the Momentum factor (Jegadeesh and Titman (1993); Carhart (1997)[1]. The academic factors are not investable portfolios and serve little use to investors looking for an easy-to-implement strategy. Van Vliet and Koning 'Conservative Formula' is an attempt to create this easy-to-implement strategy exposed to multiple factors.

After showing evidence of the low-volatility anomaly in Indian equities, we find that a conservative portfolio consisting of 100 low-risk stocks with high net payout yield and positive price momentum returned 24% since 2006. The performance is persistent over time. Additionally, it outperforms a portfolio of speculative stocks with the opposite characteristics (high risk, low net payout yield and negative momentum) by 17% over the sample period. We estimate the trading costs and show that the returns hold the nett of fees. Finally, this conservative investment strategy gives simultaneous positive exposures to multiple factors. Generally, it beats all Fama-French combinations of common investment strategies based on size, value, profitability, investment and momentum. In addition, the conservative portfolio performs well across regimes and against single and

[1]There are other factor specifications such as Hou et al. (2015), AQR, Barra.

multi-factor factor strategy indices available in India.

We contribute to the growing body of evidence-based research on factors in Indian equities. Specifically, we provide evidence of the low volatility anomaly using a broad universe of over 4000 stocks in the Indian stock market between 2006 to 2022. Second, we decompose the returns using Fama-French 5, Momentum and a self-constructed Low-volatility "factor" for Indian equities showing a complete factor decomposition for the formula. Third, we explore variation in returns of the conservative portfolio over different economic regimes in India. Fourth, we add to the literature by reporting on the Conservative Formula's turnover trends and estimating transaction costs for strategy. The nett-of-costs returns will be of particular interest to the practitioner.

Finally, this paper adds to the growing awareness of India as a market for international investors with exposure to low-volatility strategies. India indexes by global index providers often serve as the investable universe for such investors. These indices usually focus on the Large and Mid Cap firms in India with less than 200 firms. Using a broader universe of over 1,000 firms in India, we show that diversified portfolios can be constructed after accounting for impact costs. Indian equities remain reasonably independent from international markets for a variety of reasons. This paper shows that a factor-based portfolio with attractive characteristics can be constructed using Indian equities. Additionally, the findings offer independent validation of the low volatility anomaly and the conservative formula.

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

2 Literature Review

Van Vliet and Blitz (2018); Blitz et al. (2019) explored the Conservative Formula in detail. The low-risk anomaly is at the Formula's core: risk is not linearly related to returns. Ang et al. (2006, 2008); Blitz and van Vliet (2007); Baker et al. (2011); Baker and Haugen (2012); Blitz et al. (2013); Frazzini and Pedersen (2014); Auer and Schuhmacher (2015) show evidence of this anomaly using different risk metrics, including idiosyncratic volatility, realised volatility and beta measures across different markets, periods and asset classes. Agarwalla et al. (2014); Joshipura and Joshipura (2016); Joshipura and Peswani (2018); Peswani and Joshipura (2019); Ali and Badhani (2021); Peswani and Joshipura (2022) find evidence of the low-risk anomaly in the Indian equity markets. However, other researchers have questioned the anomaly. Bali and Cakici (2008) in response to Ang et al. (2006) demonstrate that the data frequency used to estimate idiosyncratic volatility, the weighting scheme used, the breakpoints utilised to sort stocks, the screens used for selection, and liquidity determine the existence and significance of a relationship between risk and returns. They conclude "*that no robustly significant relation exists between idiosyncratic volatility and expected returns*'. Huang et al. (2010) argue that short-term monthly return reversals explain the findings of Ang et al. and Bali and Cakici both. Control risk reversals, and the low-risk anomaly disappears. Pandey and Sehgal (2017) using a dataset of 493 stocks between March

2000 and November 2013, observed no volatility anomaly in India. Aziz and Ansari (2017) using data of S&P BSE-500 firms between April 1999 and June 2014, conclude a positive relation between idiosyncratic volatility and stock returns with some caveats. Ali et al. (2021) using a data set of 3,085 stocks between Jan 2000 and December 2019, report a "strong negative risk-return relationship across different risk proxies". They attribute the anomaly to being caused by "small and less liquid stocks having low institutional ownership and higher short-selling constraints". While a lively debate on the low-volatility anomaly continues, the evidence of some convexity in the relationship between risk and return continues to grow. Dedicated low-risk investing is now largely an accepted investment approach labelled *low-volatility*, *managed volatility*, *minimum volatility*, *minimum variance*, *defensive*, or *conservative*.

While there is no single unified umbrella theory to explain the low-volatility anomaly, academics use rational and behavioural aspects to explain the anomaly. Blitz et al. (2019) provide five possible explanations:

- **Constraints**: The low-risk anomaly has been linked to the limits to arbitrage arising from practical constraints, particularly the reduced ability to short and leverage low-risk assets. Brennan (1971) argued that the security market line (SML) might be flatter than predicted by the Capital Asset Pricing Model (CAPM) in the presence of leverage constraints. Under CAPM, there is a single "efficient" portfolio, and investors add leverage depending on their risk aversion. As a consequence, investors looking to increase returns are forced to look at adding high-beta securities, which increases the demand for high-beta securities and is one possible explanation for the SML's flattening. Frazzini and Pedersen (2014) found that the low-risk anomaly tends to be stronger when leverage constraints are tighter. Within the Indian context, structural leverage constraints arise from regulation on short-selling and market structure.

- **Relative performance objectives**: Another explanation for the low-risk effect is the focus of investors on performance relative to others instead of absolute performance.Blitz et al. (2014) posits a two-stage investment process, where investors first make asset allocation decisions based on absolute performance criteria and then switch to a relative performance objective when trying to identify the best managers or securities. This construct assumes a mental accounting bias described in Shefrin and Statman (2000) where "*the low-aspiration layer is designed to avoid poverty, while the high-aspiration layer aims for a shot at riches*".

- **Agency issues** Baker and Haugen (2012) describe this agency problem. They argue that all portfolio managers/analysts implicitly or explicitly have option-like reward structures, incentivising them to focus on high-risk assets lowering the demand and, therefore, the ability to arbitrage away the excess returns of low-risk assets.

- **Skewness preference**. Some investors seem to behave as risk-seekers, with a preference for lottery-like payoffs or positive skewness (Blitz and van Vliet, 2007). Kumar (2009) argues that many retail investors participate in the stock market to gamble. To such investors, high-risk stocks are attractive as they offer the hope of significant upside with seemingly limited downside. Investors who prefer skewness are willing to pay a premium to take the risk instead of demanding compensation. Shefrin and Statman (2000) argue that such investors tend to overpay for risky, lottery-like stocks and do not pay much attention to stocks with low volatility resulting in an overpayment for risky stocks, reducing their returns while keeping the upside of low volatile stocks intact. Individual retail investors dominate the Indian equity market, with many demonstrating skewness preferences.

- **Behavioural biases**: Behavioural biases, such as attention-grabbing bias, representativeness bias, benchmarking and overconfidence, may cause investors to irrationally "prefer" higher-risk stocks over lower-risk stocks

There is, therefore, a significant body of evidence and a preliminary theoretical framework for the low-risk anomaly. Factor theory has even broader support starting from the work of Fama and French (1993). Low volatility is not yet widely accepted as a factor in its own right. Despite that, given its growing popularity in investment management, rigorous testing of the conservative formula in India would interest asset managers and asset owners alike.

3 Methodology and Data

3.1 Methodology

Van Vliet and Blitz (2018) adopt a straightforward process using market data to construct the Conservative portfolio. At the end of each quarter, the 1,000 largest stocks by market capitalisation are selected and split into groups of 500 stocks each, based on the realised 3-year stock return volatility. Each stock is then further ranked on its momentum (following Jegadeesh and Titman (1993), the 12-1 month price momentum) and total net payout yield - NPY - (Boudoukh et al., 2007). This yield consists of the dividend yield and the net charge in outstanding shares as a percentage of the prior 24-month average shares outstanding. An aggregate rank, the average of the momentum and NPY ranks, is computed for each stock. The top 100 ranked stocks are equally weighted to make the "Conservative" portfolio. Van Vliet and Blitz create an opposite "Speculative" portfolio by "*selecting from the 500 stocks with the highest volatility those stocks with the weakest combined scores on momentum and NPY*. So do we. The conservative portfolio is rebalanced quarterly to "limit turnover".

Our universe, from Worldscope, has over 4,100 firms listed on the NSE or BSE. In March of each year, from this universe, we select firms listed as "active" with positive net worth and have a market cap at the end of March of at least 10% of the overall market median. Starting from September 2006, at the end of every quarter, we select the largest 1,000 stocks by market capitalisation on the last trading day of the quarter from the broader universe of relevant stocks for the period. We rank each of these 1,000 firms by 3-year volatility. If the firm does not have 3-year price data, we exclude the firm without replacement. Table 1 summarises the firms' statistics for our observation period. To create conservative and speculative portfolios, we adopt the rest of Van Vliet and Blitz process of ranking stocks by momentum and NPY to select the top and bottom 100 stocks. All portfolios are equal weighted[2]

[2]We have also run the analysis using market-weight portfolios. While the details differ, the conclusions are similar.

To examine the existence of the low-volatility anomaly in the Indian market, we adapt Blitz et al. (2013) and align the approach to the conservative formula construction. At the end of every quarter[3], we build 10 equally weighted decile portfolios by dividing the stocks based on the past three-year realised volatility. The top-decile portfolio consists of the lowest historical volatility stocks, whereas the bottom-decile portfolio comprises stocks with the highest historical volatility. Portfolios are held for a quarter.

We calculate monthly total returns in Indian Rupees for each conservative, speculative, and decile portfolio. As these are quarterly portfolios, the monthly return will affect stock weights in the portfolio between two rebalancing periods. Some stocks may de-list or be suspended during the holding period. We reflect this as that portion of the portfolio retaining the last traded value until the next rebalance cycle, where the new equal-weighted portfolio is constructed.

To test the statistical significance between Sharpe ratios, we use the test of Jobson and Korkie (1981) with Memmel (2003) correction (JKM test):

$$Z = \frac{SR_1 - SR_1}{\sqrt{1/T \cdot \left[2(1-\rho_{1,2}) + 1/2 \cdot (SR_1^2 + SR_2^2 - SR_1 \cdot SR_2(1+\rho 1, 2^2 \right[}} \tag{1}$$

Where SR_i is the Sharpe ratio of portfolio i, $\rho_{i,j}$ is the correlation between portfolios i and j, and T is the number of observations. The excess returns to calculate Sharpe ratios is a compounded return.

3.2 Data

All our base firm-level data is from Refinitiv and Datastream and start from March 2006 except for prices which start from 2003. Market capitalisation, closing prices, 3-year realised volatility, and outstanding net shares are gathered monthly. Other than outstanding shares, the rest of the relevant data variables are denominated in Indian Rupees. The 3-year volatility is computed using weekly returns; the dividend yield is the trailing twelve-month yield. The total net payout yield to shareholders is the dividend yield and the net change in shares outstanding. There is minimal survivorship bias in the data as it includes all firms, including those de-listed or amalgamated/merged. For the single or multi-factor strategy indices, we get the total return series from the websites of the Nifty Indices[4] and S&P Dow Jones Indices[5]. The TR series of the sample indices all start from September 2006.

We use the monthly data from Data Library: Fama French 3 and 5 Factors and Momentum Factor for the Indian Market (Raju, 2022)[6] with data till June 2022 as our Factor dataset. The risk-free rate is computed using

This analysis is not presented in this paper.

[3] Blitz et al. construct a monthly portfolio while we adopt a quarterly holding period.

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

[5] https://www.spglobal.com/spdji/en/

[6] https://invespar.com/research

the 91-day T-bill rate sourced from the Reserve Bank of India's weekly auction data available at Refinitiv[7]. The implied yields are converted to monthly rates. For the Low-Volatility factor, we construct monthly returns using 36-month volatilities following the Fama and French (2015) construction and breakpoint methodology.

4 Results and Discussion

4.1 Empirical evidence for the Low-Risk Anomaly in India

Blitz et al. (2013); Joshipura and Joshipura (2016) show the existence of the low-risk anomaly in India. Specifically, if the relation between risk and return is linear, the risk-return curve should monotonically increase as risk increases. We construct decile portfolios of increasing realised 36-month realised volatility, where decile 1 is the lowest volatility portfolio and decile 10 is the high volatility portfolio. Figure 1 shows the risk-return characteristics using excess returns over the risk-free rate across the portfolios and a polynomial line of best fit. The relationship between risk and return is not upward sloping and even inverts at higher risk, providing evidence of the low-risk anomaly, similar to the findings of Blitz et al. (2019). Table 2 breaks down the composition of each decile portfolio using the Fama French breakpoint for size[8]. *Small* stocks dominate the higher-risk portfolios.

Therefore, a reasonable question is whether the low-risk effect is restricted to large-cap stocks? Figure 2 breaks down the excess return and risk characteristics for 5x5 Size-Volatility portfolios. The 1,000 stocks are first sorted in 5 Size sorts using the 3rd, 7th, 13th and 25th percentiles of the aggregate market capitalisation for the relevant quarter (Fama and French, 2015). Within these five Size sorts, the stocks are ranked in order of lowest 36-month volatility, and five portfolios in order of rank built. The 5x5 portfolios, therefore, show the risk-return relationship by Size. While the relationship is expectedly more noisy than Figure 1, the generally negative at higher volatility nature of the relationship holds across the Size sorts. The smaller-size firms show a higher risk for equivalent volatility sorts. Figure 2 also summarises the number of stocks in each size sort: expectedly, the top 1,000 market-cap firms are dominated by the smaller market cap firms. As an alternative, and as a robustness test, Figure 3 shows the 1,000 stocks sorted into five categories, each having approximately 200 stocks. The table in the figure shows that the mean market cap is lower across the sorts as many very small-cap stocks are spread out across the size sorts. Visually, the low-volatility anomaly is seen across this sorting schema as well. Consequently, in the Indian context, the low volatility anomaly is not a large-cap phenomenon. While we do not do a detailed statistical analysis, it is evident that in both 5x5 portfolios, the relationship between risk and return is not upward sloping. It generally shows a negative or a flat relationship.

The findings align with a large number of international studies showing the existence of the low-volatility anomaly. As the conservative formula is predicated on this anomaly, we better understand the reason for the formula's performance by evaluating the risk-return characteristics of portfolios built using the same method-

[7]Also available at http://dbie.rbi.org.in/DBIE/dbie.rbi?site=statistics, under Financial Market» Government Securities Market.

[8]Big stocks are those in the top 90% of March market cap, and small stocks are those in the bottom 10%.

ology.

4.2 The Conservative Formula: Summary

Van Vliet and Blitz (2018) show that the conservative formula exhibits "*much lower risk than the speculative portfolio, yet much higher returns*" across all the regions they studied. Similar to their findings, Figure 4 shows that *ex-post* risk for the systematic portfolio using the conservative formula is low. By implication, realised volatility serves as a good indicator of future risk. In the Indian context, for the full sample, the risk reduction is 43%, within the range of risk reductions reported by Van Vliet and Blitz ("*50% for the US and Emerging Markets...35% in Europe and Japan*"). The return difference is also significant (17%) and comparable to the difference between the two comparable portfolios for Emerging Markets computed in Van Vliet and Blitz (2018). The JKM test statistic for the Sharpe ratios of the Conservative Portfolio (0.74) and the Speculative Portfolio (0.01) for the full period is -14.84. In other words, the Conservative Formula in the Indian context offers a consistently higher return-to-risk ratio than the Speculative counterpart.

In addition, Figure 4 shows the risk-adjusted returns for the market-weighted portfolios created using the same rules as the equal-weighted Conservative and Speculative portfolios and the S&P BSE 100 total return index. The difference between the equal-weighted and market-weighted Conservative portfolios indicates that the returns more than compensate for the additional risk from the equal-weighted portfolio. On the other hand, the market-weighted Speculative portfolio has the same risk but significantly lower return. Portfolio weights do play a role in outcomes. Irrespective of the weighting schema, the benefits of the Conservative formula are visually evident. The equal-weighted Conservative portfolio delivers a significantly higher risk-adjusted return than the market-weighted S&P BSE 100. Even the market-weighted variant shows a higher return with lower risk than the market index.

4.3 The Conservative Formula: Results Over Time

A ₹1,000 investment in the S&P BSE 100 Index at the end of September 2006 would have grown[9] ₹5,394 at the end of June 2022 (a continuously compounded rate of 11.3% pa). The Conservative Formula portfolio has a terminal wealth that is almost 6 times higher compared to the NIFTY 50 (₹30,818 , with a continuously compounded return of 24.3% pa). By contrast, the Speculative portfolio has a more modest 6.9% pa compounded return. Visually, Figure 5 shows that the wealth development of the Conservative Formula portfolio is robust over time. There has been an acceleration of returns post-covid, and even discounting the more recent trend, the long-term outperformance is evident.

Figure 6 shows performance over five-year intervals. Though the period is short (16 years or 190 months), the average annual total return ex-costs and taxes for conservative stocks is consistent: exceeding the market

[9] Gross total returns before costs, such as, but not limited to, transaction costs, slippages, taxes, implementation costs and adverse market timing.

proxy (S&P BSE 100) and with no negative 5-year period. The Speculative portfolio shows a weaker picture: inconsistent, negative average 5-year rolling when period start date was between 2006 and 2010, and underperforming the S&P BSE 100 in 2 of the three periods.

The figure also shows the development of the market-weighted variants for the Conservative and Speculative portfolios. The market-weighted Conservative portfolio lies between the equal-weight Conservative portfolio and the S&P BSE 100, while the market-weighted Speculative portfolio has the worst trajectory among the five portfolios.

4.4 Comparison with Fama-French portfolios

As factors explain a significant portion of equity portfolio returns, we compare the risk-return characteristics of the conservative formula with factor portfolios. Specifically, we use the double-sorted (2x3) Fama-French (FF) factor portfolios from Raju (2022)[10], who adapted the work of Fama and French (2015) for Indian equities. Using the same universe of firms, we created low-volatility portfolios based on 36-month realised volatility and the same breakpoints as in Fama and French (2015). Figure 7 shows that the Conservative Formula has the highest Sharpe ratio compared to all other Fama-French factor-combination strategies[11]. This finding is similar to Van Vliet and Blitz (2018).

The FF5, Momentum and Low-Vol portfolios are value-weighted, while the Conservative portfolio is equal-weighted. Unlike the Conservative portfolio, which has a lower bound on market cap, the FF, Momentum and Low-Vol portfolios hold firms across a range of market cap. Figure 8 shows the breakdown of the firms in the portfolio formed using the Conservative Formula using the Fama-French size breakpoint. While there is a *Big* bias, the range of such firms (Max:80; Min:32; Mean 60) has some critical implementation implications that we will deal with later.

4.5 Factor Exposures of Conservative Minus Speculative (CMS) Portfolio

The return spread between the Conservative and Speculative portfolios in our sample is 17.4% per year. We regress these returns of the Conservative Minus Speculative (CMS) Portfolio against a range of factors: from the 1-factor CAPM to a 7-factor model consisting of the 5-Factor Fama-French model (Fama and French, 2015), the Momentum Factor Jegadeesh and Titman (1993), Car1997 and a self-constructed Low-Volatility "factor" (Blitz and van Vliet, 2007). Table 3 shows various regression outcomes between September 2006 and June 2022. The CMS portfolio has a full-sample CAPM annualised alpha of 17.7%. As CMS is long low-volatility stocks and short high-volatility stocks, there is a large and significant negative market beta coefficient. The alpha using the traditional Fama-French 3-factor model is almost the same (17.5% annualised). The negative size, SMB, the coefficient in the 3-factor decomposition, shows that CMS is exposed to *Big* size - inherent in the design of the conservative formula. Ang and Chen (2007) argue that over the long run, value stocks are more volatile and

[10] Avaliable at `https://invespar.com/research`
[11] We do not report the JKM Z statistic in the paper, but note the statistic is significant.

have higher betas than growth stocks". Aligned to this perspective, the value factor, HML, is negatively loaded in the FF3 decomposition. As momentum is integral to the conservative formula, when momentum, WML, is added to FF3, the 4-factor alpha expectedly drops (to 7.9% annualised). In all cases, the alpha is statistically significant, and the Adj R-squared monotonically increases from CAPM to the 4-factor model.

The conservative formula's final pillar is NPY - which we argue is a measure of quality in a broad sense[12]. The Fama-French 5-factor model (Fama and French, 2015) adds operating profitability, RMW, and Investment, CMA factors to FF3. Table 3 shows that the conservative strategy has positive loadings on both these new factors. The negative loadings to the market factor, the size factor, SMB, and the value factor, HML, persist. Compared to FF3, FF5 has a higher Adj. R-squared and alpha drop to, 7.9% annualised. When we additionally control for the momentum factor (another positive loading), the Adj. R-squared is even higher, and the 6-factor alpha is further reduced (5.5% annualised) and less significant. Our results show a negative exposure to the value factor, HML. In Van Vliet and Blitz (2018), the FF3 long sample (1926-2016) regression has a negative loading on HML, while the short sample (1963-2016) FF5 regression has positive loading on HML[13]. Our findings align with a sample-dependent HML loading, implying that the relationship with HML is dynamic. In all other aspects of factor decomposition of CMS, our findings are aligned to the findings of Van Vliet and Blitz (2018). While statistical analysis is needed to understand the difference, we posit that India's growth characteristics reinforce the argument by Ang et al. (2006) and low-volatility companies in India will not be traditional value firms. Finally, adding the low-volatility "factor", the 7-factor model shows no alpha. The market factor exposure is negative but insignificant, as low volatility does the heavy-lifting in this decomposition. All the elements of the conservative formula, low-volatility ($LVOL$), momentum (WML) and "quality" (RMW and to a lesser degree CMA) are evident and statistically significant.

Most investors would like to see factor tilts in their portfolio since all these factors are associated with diversified and, possibly, higher returns. The conservative formula shows strong evidence of a multi-factor portfolio, using three variables, which do not require accounting data.

4.6 Conservative Portfolio performance across regimes

Following Luk and Jain (2017), we use the Composite Leading Indicator (CLI) for India published by the Organization for Economic Co-operation and Development (OECD). The CLI is designed to provide early signals of turning points in business cycles showing short-term fluctuation of the economic activity around its long-term potential. We identify four expansionary periods (Oct 2006 - Sep 2007, Apr 2009 - Dec 2010, Jun 2013 - Sep 2018 and May 2020 - Jun 2021) and contraction periods (Oct 2007 - Mar 2009, Jan 2011 - May

[12] Although we do not present the results, in the Indian context, the dividend yield has dominated NPY during our observation period. As the Indian equity market matures, given the difference in the tax rates for dividends and long-term capital gains, we expect the firms in India will follow the path of US firms where share-buybacks are popular.

[13] Mr. Pim Van Vliet commented when reading an earlier draft of the paper the "*loading on HML was not very stable in US and international markets. It depends on the sample*".

2013, Oct 2018 - Apr 2020 and Jul 2021 - Jun 2022). Figure 9 shows the Sharpe ratios for the Conservative and Speculative portfolios and the S&P BSE 100 for each period. Across all periods, the Conservative portfolio does better than the S&P BSE 100. The Speculative portfolio beats the Conservative portfolio in one expansionary phase but underperforms in the other three. The Speculative portfolio underperforms the Conservative portfolio in all other regimes. The Speculative portfolio does better than the S&P BSE 100 in two expansionary periods but is flat to or worse than the index in all other periods. These drawdowns contribute to the development of the wealth index in Figure 5 for the Speculative portfolio - all the gains during the expansionary phase are given up during periods of contraction. The Conservative portfolio negotiates reasonably nimbly contraction periods, with negative performance equivalent to the S&P 100 BSE. Therefore, the Conservative portfolio is the preferred portfolio of the three.

4.7 Comparison with single factor and multi-factor index portfolios

Following the work by Fama-French and others, theoretical factor studies typically consider a long-short portfolio which, unfortunately, does not translate into implementable or tradable strategies. In practice, factor strategies are often implemented using a long-only method. Index providers in India offer several factor strategy indices. While the results of the Conservative portfolio are encouraging, how do they compare against existing single and multi-factor indices available in India? We directly compare the Conservative Formula to other single/multi-factor strategies from two of India's largest index providers: Nifty Indices and S&P Dow Jones Indices (through Asia Index Private Limited). As these indices usually hold around 30-50 holdings, we include the results of a Conservative portfolio containing 30 stocks using the same methodology: equally weighting 30 top stocks from the universe consisting of the largest 1,000 stocks. As the indices total return performance before costs and taxes comparing the performance is on a like-for-like basis.

Figure 10 shows that the Conservative Formula and the Conservative 30 portfolio have higher entire period Sharpe Ratios than those of the indices[14]. Both variants of the conservative portfolios show higher returns across the sample period than the single/multi-factor indices. They also have risks comparable to the momentum, low-volatility, and quality portfolios. There is a significant difference in the simple and compound returns of size, value and momentum indices. This difference arises from the investment horizon[15], and the table in Figure 10 shows that the assumed investment horizon, which determines the average return, for most investors is longer than 1-month (simple return) but shorter than the total sample (compounded return). The higher volatility of the strategy will determine some of the return drag. Following Van Vliet and Blitz (2018), we de-risk all factors to the same volatility level as for the Conservative Formula (22.6%). For example, the de-risked Nifty Small Cap100 strategy invests for 71% in stocks and 29% in the risk-free asset to have the same risk as the Conservative portfolio. This approach converts Sharpe ratio differences into return differences[16]. Both variants

[14]The Sharpe Ratios of both portfolios have significant JKM test z-statistics compared to the Sharpe ratios of the sample indices.

[15]Arithmetic versus geometric means.

[16]The de-risking explains most of the return drag due to compounding, but not all since the return drag consists of volatility effects and autocorrelation effects. The volatility effects are easily calculated using $0.5 \cdot \sigma^2$ where σ is the standard deviation of the strategy.

of the Conservative Formula have the highest return per unit of risk compared to all other strategies. This difference can be attributed to the integration and diversification benefits of combining multiple factors into one strategy using the Conservative Formula.

Figure 11 compares both variants of the conservative portfolio against the commercial single and multi-factor strategy indices. Visually, the Conservative strategy performs consistently across expansion and contraction regimes.

4.8 Trading Costs and implementation considerations

Can the observed conservative formula's 10.3% FF5 alpha survive transaction costs? Turnover is the most important driver of transaction costs (Novy-Marx and Velikov, 2014). Given the relatively shallow equity market liquidity for most parts of the market, impact costs are another source of slippage in India. Following quarterly rebalancing, the conservative formula is designed to reduce turnover and limit the impact of the transaction cost. Figure 12 shows the one-sided quarterly turnover over the sample period. The average turnover per quarter is 33% and the mean *Small* cap stocks (from table 2) is 38. There are two components of turnover costs:

- **Brokerage**:Assuming a 20 bps brokerage commission for each leg with around 33 changes per quarter, the annual brokerage drag would be about 0.50%[17].
- **Impact cost**: These are the costs due to increased bid-offer spreads when the quantity traded is relatively significant. These costs are costs of liquidity. Assuming all our turnover is from *Small* and the impact costs for such firms is 50 bps[18], the impact estimate is around 1.30%[19]. We have not modelled the capacity limits for the Conservative formula resulting from thin liquidity pools of *Small* size stocks in India.

Therefore, our conservative estimate of costs is around 1.8%, well below the FF5 alpha[20]. The conservative formula will likely survive implementation in India[21]. More optimised trading strategies will reduce turnover further, but we leave that to practitioners to explore.

The conservative formula is an active strategy. It is not a value-weighted portfolio, nor is it a buy-and-hold schema. The choice of risk metric, the look-back period, the number of holdings, the weighting method, and the rebalancing frequency are all operational decisions that will contribute to the "craftsmanship alpha" (Israel et al., 2017) of the formula. Such large-number-of-holdings systematic strategies have significant operational risks associated with their implementation. In general, and more so in a top-heavy market like India, liquidity

[17] 33 stocks ÷ 100 stocks x 2 legs x 4 quarters/year x 20bps

[18] We have been conservative in the impact costs. See estimates of impact costs by NSE available at `lhttps://www.niftyindices.com/reports/monthly-reports`.

[19] 33 stocks ÷ 100 stocks x 2 legs x 4 quarters/year x 50bps

[20] We ignore taxes in the analysis. The impact of transaction-related taxes is negligible, while capital-gains taxes are subject to investor circumstances.

[21] The FF5 alpha for the Conservative 30-holding portfolio is 7.7% . It has a turnover that is slightly higher than the 100-holding Conservative formula at 37% (or 11 stocks). This portfolio has an average holding of 4 *Small* stocks. This translates into a total slippage (brokerage and impact costs) of just over 1.1% ([11 ÷ 30 x 2 x 4 x 20 bps] + [4 ÷ 30 x 2 x 4 x 50 bps]) leaving enough alpha to survive implementation. The 30 holding variant has, expectedly, lower exposures to factors than the 100-stocks variant of the conservative formula.

dries quickly as one goes down the market cap. Strategies which require exposure to less liquid small-cap firms in India hit capacity constraints very quickly. The conservative formula will hit size constraints based on the volume traded by the smallest firms by market cap held on any rebalancing. The effect of other strategy indices rebalancing on the same days also affects capacity. The previous section notes that most strategy indices have the top 200 stocks as their universe. They all tend to rebalance quarterly or semi-annually on crowded days - which constrains capacity further[22]. Blitz and Marchesini (2019) argue that systematic factor strategies with more significant investment amounts need to apply trading strategies that use the liquidity in the market more efficiently throughout the year, rather than stick to infrequent but regular days of the calendar. Consequently, any implementation will require careful consideration of the unique market liquidity structure of Indian equities.

4.9 Comparing the Conservative Formula with other popular styles

We finally turn to compare the results of the conservative formula with other popular styles in India. In particular, we examine the performance against existing research or replications of the Magic Formula (Greenblatt and Tobias, 2005) and the Coffee-Can Portfolio in India. Replication studies for these formulas use a smaller universe of stocks and are for more limited periods. To allow reasonable, but not statistical, comparisons, we have aligned periods and, where possible, the calculation methodology.

Using the S&P BSE 500 stocks as their universe, Preet et al. (2021) replicate the Magic Formula between 2012 and 2019 for India. They report that the average return of a 30-stock equal-weighted Magic Formula portfolio is 17.7%, the compounded period return is 13.9%, and a standard deviation of 33.33%[23]. Using their method to calculate returns[24], for the period between July 2012 and January 2020, the 100-stock conservative formula has 26.4% average return pa, 23.0% ann. compounded period return, and standard deviation of 27.9%, while the 30-stock Conservative portfolio has 18.6% average return pa, 16.8% ann. compounded period return, and standard deviation of 16.5% return. Without doing a complete statistical analysis, for both the Conservative portfolios, one can reasonably conclude that the conservative formula delivers better risk-adjusted and absolute returns than the Magic Formula for the period.

Ambit Asset Management runs a Portfolio Management Scheme (PMS) named "Ambit Coffee Can Portfolio" (ACCP) using the Coffee Can Portfolio model. ACCP is a concentrated 10-15 stock portfolio where the fund managers exercise discretion in the portfolio construction. The PMS update for June (Amb) provides a detailed report on their approach and results. The report covers performance from inception (6 March 2017) till the end of May 2022. As this is a "live" portfolio, comparing it to our theoretical model is challenging. We include transaction costs for the Conservative 100- (1.8% pa) and Conservative 30-stock (1.1% pa) portfolios. In addition, we add a further 1% pa to reflect additional costs and fees. These costs are deducted from the monthly returns for the two portfolios. (Amb) reports returns net of costs and fees as 17.6%, the standard

[22]see Raju and Krishnan (2022).

[23]Preet et al. report that the Magic Formula has a higher standard deviation than the S&P BSE Sensex. Their calculated Sharpe Ratio of the Magic Formula is 0.31 for the period.

[24]Preet et al. calculate annual returns between July of the previous year and June of the current year.

deviation of 15.3% and a Sharpe Ratio of 0.8[25]. Incorporating costs and fee assumptions outlined above, the statistics for the same period (March 2017 - May 2022) for the Conservative 100 (20.5% compounded return pa, 19.2% ann. standard deviation, and 0.81 Sharpe Ratio) and the Conservative 30 (17.4% compounded return pa, 15.7% ann. standard deviation, and 0.79 Sharpe Ratio) are broadly comparable[26].

5 Conclusion

We implement The Conservative Formula proposed by Van Vliet and Blitz (2018) that is "*designed to make quantitative investing easy for investors*" for the Indian stock market using data from 2006 onwards. The Conservative Formula uses three simple investment criteria that are not susceptible to accounting and other differences across countries, making its application potentially universal across equity markets. The Formula gives an investor multi-factor exposure via a portfolio of 100 stocks in the most liquid part of the market with ease of implementation and transparency. Despite its simplicity, the Formula exposes three well-regarded factors: Low Volatility, Quality and Momentum. We show that the Formula likely survives implementation costs given its low unoptimised turnover. Our findings add India to the US, Europe, Japan and other Emerging Markets, which show the outperformance of the Conservative Formula to the market portfolio. Additionally, we show the attractiveness of the Conservative Formula compared to popular single and multi-factor strategy indices available in India and other popular "formula" styles. This simple yet robust construct may interest a broad base of asset owners and managers due to its foundation in academic insight, ease of implementability and transparency.

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[25] Table in page 11 of (Amb)

[26] We caution against reading too much into this as there are several assumptions we make about the results reported in (Amb) which we try to incorporate. There is also no attempt made to optimise turnover for the conservative portfolios. A more detailed analysis is required over longer periods.

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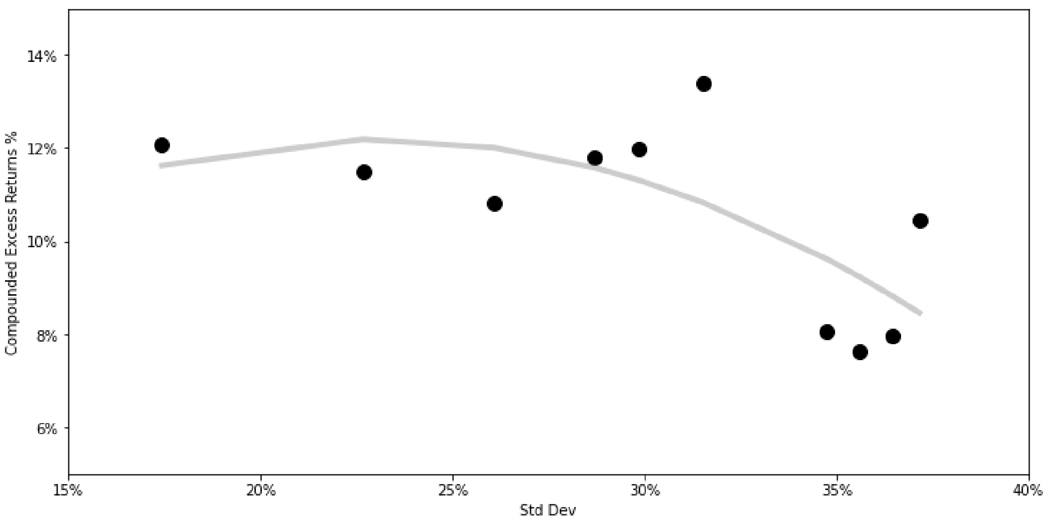
Exhibits

Table 1: Descriptive statistics of market capitalization of firms

	Total Active Firms in Universe	Top 1000 Firms by Mkt Cap	Market capitalization - percentile (Rs million) 10%	30%	50%	70%	90%	Total Mkt Cap (Rs billions)	Average Mkt Cap (Rs millions)
2006-12-31	1,704	994	1,052	1,950	4,473	11,980	50,571	31,914	32,122
2007-12-31	1,800	998	1,376	2,688	5,910	15,762	73,704	43,490	43,592
2008-12-31	1,962	999	1,296	2,343	5,319	14,135	59,755	39,964	40,003
2009-12-31	2,040	1,000	1,377	2,474	5,738	15,413	79,355	49,974	49,998
2010-12-31	2,066	1,000	2,231	4,079	8,748	23,786	117,562	64,796	64,796
2011-12-31	2,158	1,000	2,042	3,592	7,538	22,792	106,808	60,392	60,421
2012-12-31	2,270	1,000	2,056	3,632	7,652	23,090	116,433	62,484	62,516
2013-12-31	2,343	1,000	1,660	3,065	6,570	18,970	114,864	62,169	62,170
2014-12-31	2,366	999	3,006	5,904	12,232	32,355	159,592	89,712	89,804
2015-12-31	2,379	998	3,466	6,531	13,632	37,219	193,780	97,239	97,434
2016-12-31	2,414	998	4,385	7,809	16,716	41,290	197,688	101,458	101,662
2017-12-31	2,440	998	5,841	10,726	22,904	56,501	250,384	126,034	126,349
2018-12-31	2,526	996	5,812	11,577	24,210	60,527	275,552	139,610	140,242
2019-12-31	2,580	996	4,628	9,222	20,494	59,266	275,930	149,140	149,740
2020-12-31	2,524	996	4,094	7,803	17,856	55,801	269,475	144,087	144,590
2021-12-31	2,464	997	8,780	17,076	37,124	103,798	439,560	236,464	237,175
2022-06-30	2,443	999	9,468	17,394	36,637	97,209	428,838	237,799	238,037

The table shows the cross-sectional annual median of percentiles, total and average market capitalization for various period ending December 31 for firms included in our study. The market capitalization of a firm is the median capitalisation at the end of each month of the relevant year. For 2006, the data is the median for September to December 2006. Similarly for 2022, the data is the median of values between January and June. From the top 1000 firms by market capitalisation, there are some firms who will not have 3 year histories. These firms are excluded without replacement.

Figure 1: Ten portfolios sorted on 36-month realised volatility: Sep 2006 - Jun 2022



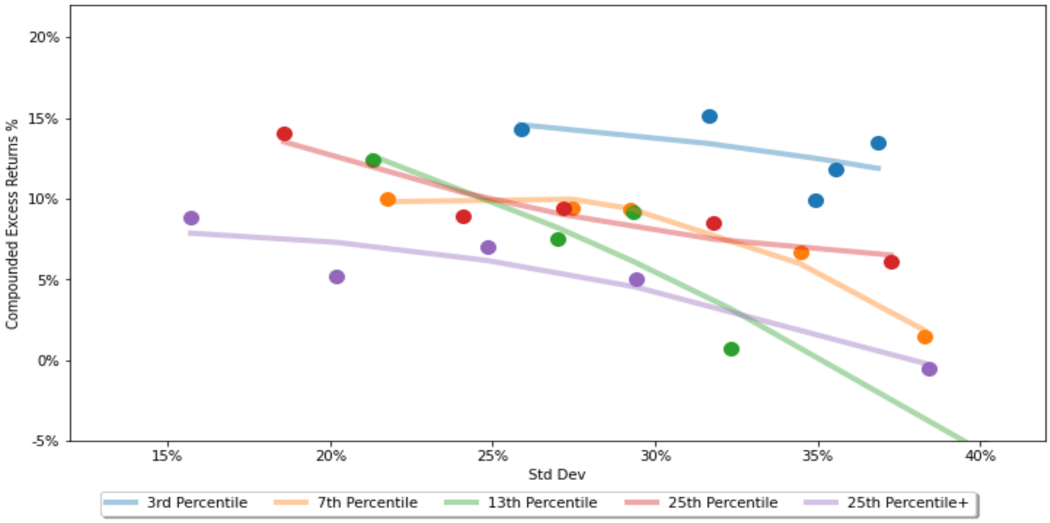
Source: Authors calculations, Refinitiv Datastream.

Table 2: Median composition of Decile Portfolios using Fama French Size Breakpoints: Sep 2006 - Jun 2022

	Big	Small	Total
Decile_1	62	38	100
Decile_2	48	52	100
Decile_3	40	60	100
Decile_4	30	70	100
Decile_5	22	78	100
Decile_6	17	82	99
Decile_7	13	86	99
Decile_8	13	86	100
Decile_9	9	89	98
Decile_10	8	92	100

The table shows the median number of firms classified as *Big* and *Small* as defined for Fama-French portfolios (Big stocks are those in the top 90% of March market cap, and small stocks are those in the bottom 10%).

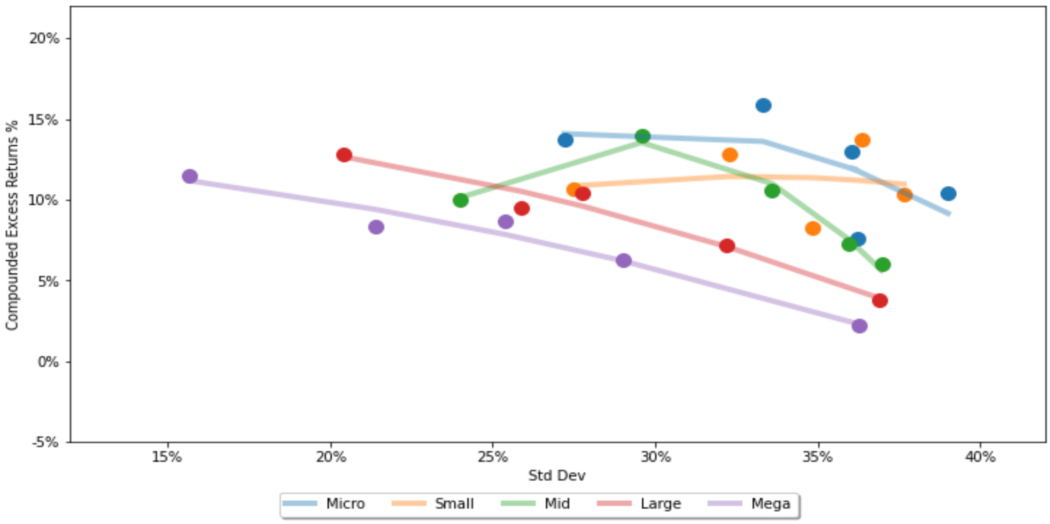
Figure 2: Fama-French 5 Size breakpoint: 5x5 portfolios sorted on size and 36-month realised volatility, Sep 2006 - Jun 2022



	3rd pct	7th pct	13th pct	25th pct	25th pct+
Mean number of firms	465	185	128	109	104
Mean Mkt Cap (Rs. Billion)	5	18	41	103	670

Source: Authors calculations, Refinitiv Datastream. The Size sorts use the breakpoints used for the five size portfolios by Fama French: the 3rd, 7th, 13th, and 25th percentiles of the aggregated market cap. The table shows the mean number of firms in each size bucket for the 1,000 firms every quarter and the mean market cap of each bucket for the entire sample period.

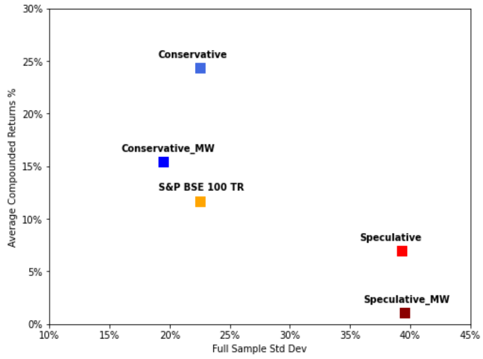
Figure 3: Equal-Number Buckets Size: 5x5 portfolios sorted on size and 36-month realised volatility, Sep 2006 - Jun 2022



	Micro	Small	Mid	Large	Mega
Mean number of firms	198	198	198	198	199
Mean Mkt Cap (Rs. Billion)	3	6	15	42	431

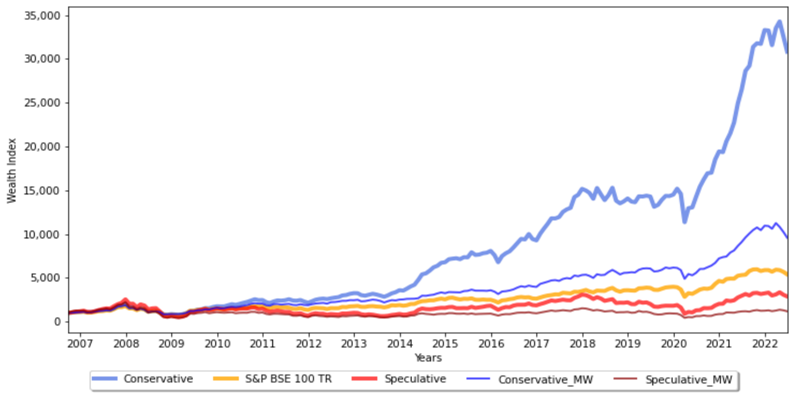
Source: Authors calculations, Refinitiv Datastream. The 1,000 stocks every quarter are grouped into buckets with an equal number of stocks based on the market cap distribution for the quarter. We have, rather unimaginatively, called the buckets: Micro, Small, Mid, Large and Mega without reference to absolute size. The table shows the mean number of firms in each size bucket for the 1,000 firms every quarter and the mean market cap of each bucket for the entire sample period.

Figure 4: Risk-Return forS&P BSE 100 TR, Conservative and Speculative Portfolios in India, Sep 2006 - Jun 2022



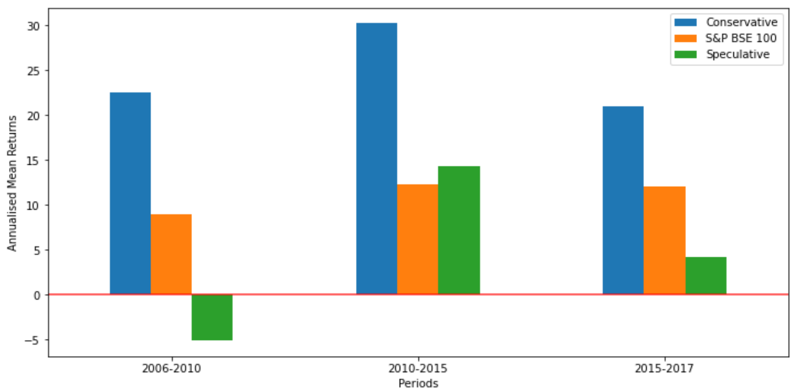
Source: Authors calculations, Refinitiv Datastream. The largest 1,000 stocks by market cap are ranked on historical 3-year volatility. From the top 500 low-risk stocks, the Conservative formula (blue) selects the 100 stocks with the best combined 12-1M momentum and net payout yield scores. The speculative portfolio (red) consists of stocks with the opposite characteristics. Portfolios are equally weighted and rebalanced quarterly. The market-weighted, quarterly-rebalanced Conservative and Speculative portfolios are suffixed with "MW". The S&P BSE 100 TR is shown separately. The average compounded return is on the vertical axis, and the standard deviation is on the horizontal axis.

Figure 5: Development of Rupee value over time for S&P BSE 100, Conservative and Speculative Portfolios in India, Sep 2006 - Jun 2022



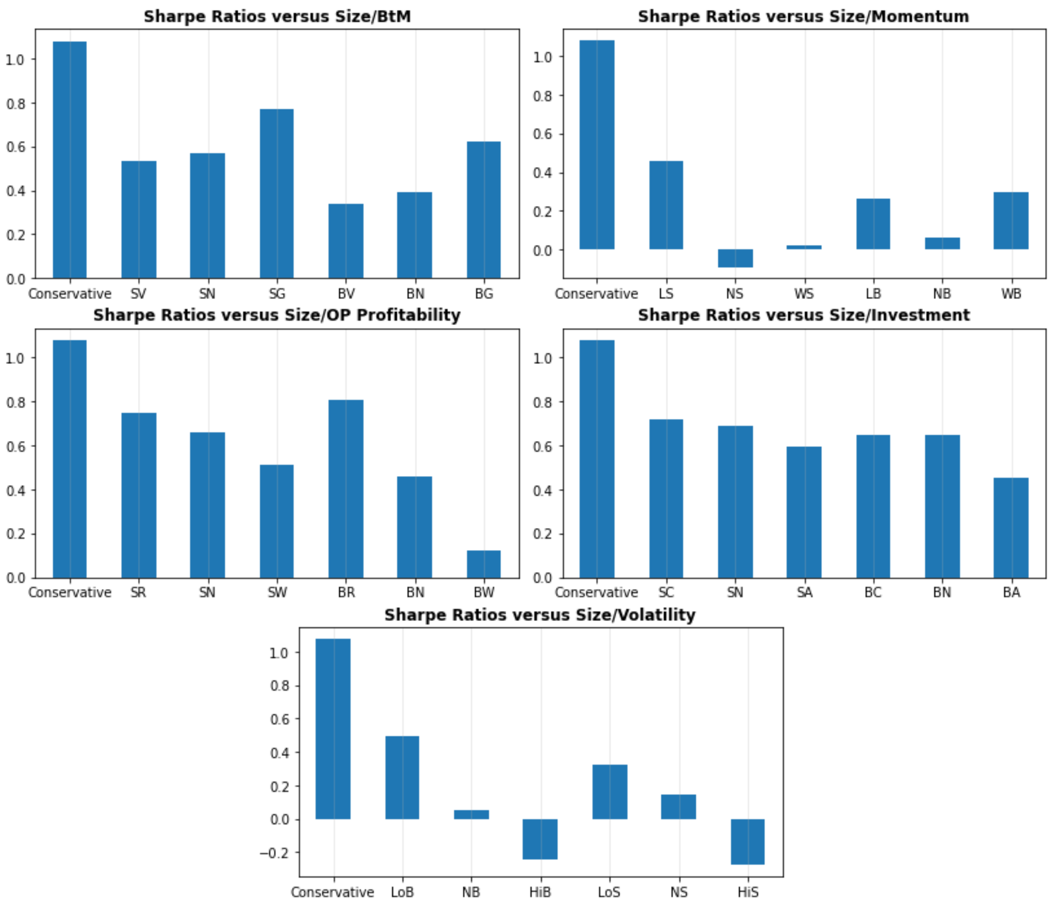
Source: Authors calculations, Refinitiv Datastream. The Conservative and Speculative portfolios each consist of 100 stocks and are equally weighted and rebalanced on a quarterly frequency. The market-weighted variants are also sown. For comparison we also show the S&P BSE 100 Index. All returns are total returns and are gross of costs and taxes.

Figure 6: 5-year rolling performance S&P BSE 100, Conservative and Speculative Portfolios in India, Sep 2006 - Jun 2022



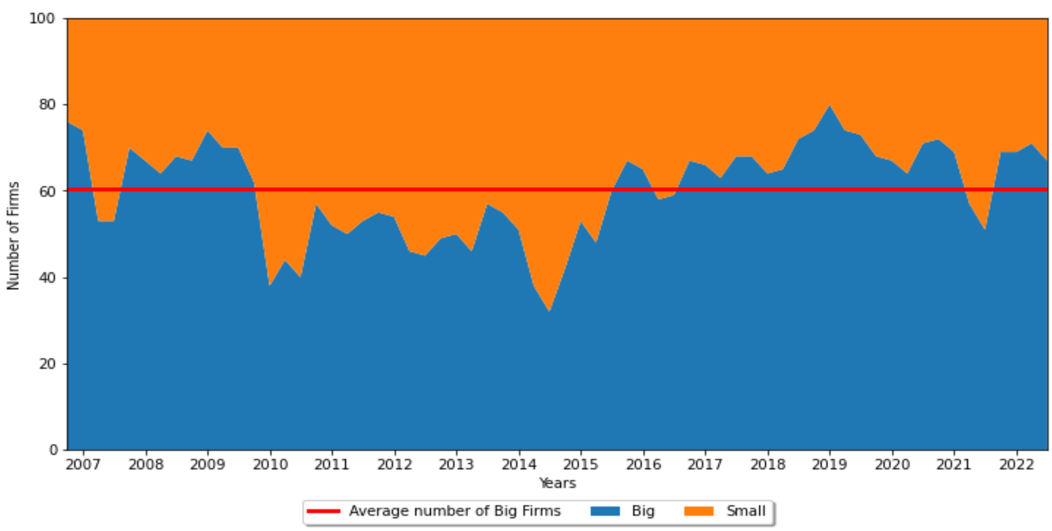
Source: Authors calculations, Refinitiv Datastream. The rolling returns are computed monthly and the 5 year periods refer to period start dates - the chart ends in 2017. The Conservative and Speculative portfolios each consist of 100 stocks and are equally weighted and rebalanced on a quarterly frequency. For comparison we also show the S&P BSE 100 Index. All returns are total returns and are gross of costs and taxes.

Figure 7: Sharpe Ratios of Conservative formula versus Fama-French portfolios, Sep 2006 - Jun 2022



Source: Authors calculations, Refinitiv Datastream, Raju (2022). The double-sorted portfolios are based on Size and Book-to-market ratio; Size and Operating Profitability; Size and Investment; Size and momentum; and Size and Volatility. See Raju (2022) fpr definitions of the first four. The authors construct Low-Volatility portfolios based on 36-month volatility and the Fama-French breakpoints (Fama and French, 2015). FF portfolios are value-weighted and include all stocks in the Raju dataset, the same as the dataset used for this study. All figures are annualized. These returns are total returns in excess of risk free rates and are gross of any costs/taxes.

Figure 8: *Big* and *Small* firms in the Conservative Portfolio in India, Sep 2006 - Jun 2022



Source: Authors calculations, Refinitiv Datastream. Firms in the conservative portfolio as classified as *Big* or *Small*. Big stocks are those in the top 90% of September market cap, and small stocks are those in the bottom 10% (See Raju (2022))

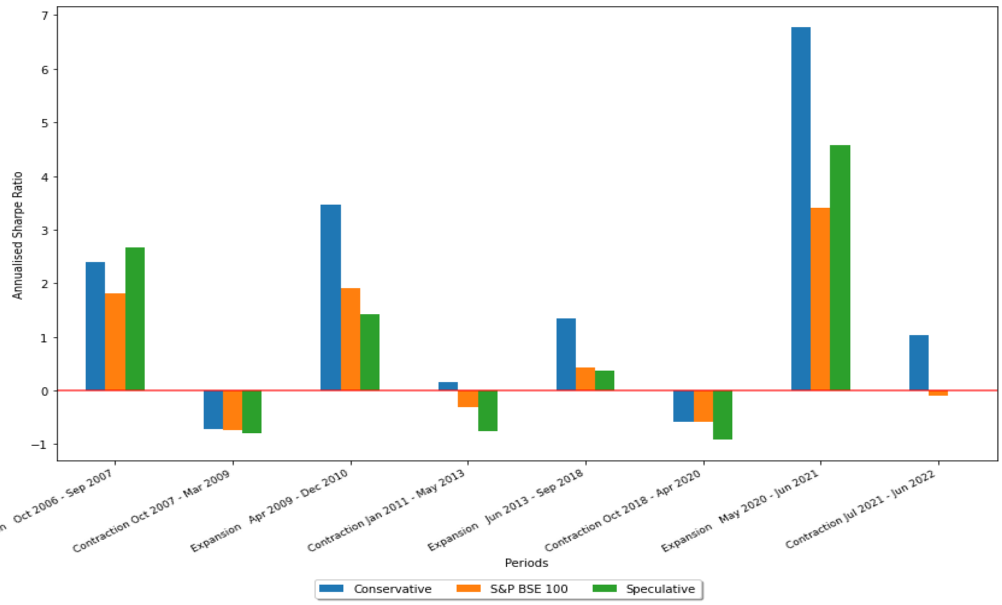
Table 3: Factor exposure of the Conservative Minus Speculative (CMS) portfolio: Sep 2006 - Jun 2022

	Dependent variable:					
	MF	FF3	FF3+WML	FF5	FF5+WML	FF5+WML+LVOL
	(1)	(2)	(3)	(4)	(5)	(6)
Alpha	0.014***	0.014***	0.006***	0.008***	0.004**	-0.001
	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
MF	-0.665***	-0.490***	-0.370***	-0.301***	-0.287***	-0.064
	(0.086)	(0.088)	(0.052)	(0.067)	(0.053)	(0.070)
SMB		-0.345***	-0.284***	-0.305***	-0.266***	-0.167***
		(0.085)	(0.066)	(0.074)	(0.065)	(0.060)
HML		-0.641***	-0.337***	-0.487***	-0.238**	-0.142
		(0.110)	(0.086)	(0.130)	(0.113)	(0.102)
RMW				0.475***	0.308***	0.183***
				(0.085)	(0.063)	(0.060)
CMA				0.847***	0.455***	0.356***
				(0.142)	(0.109)	(0.100)
WML			0.505***		0.419***	0.380***
			(0.044)		(0.042)	(0.040)
LVOL						0.410***
						(0.090)
Observations	189	189	189	189	189	189
R^2	0.503	0.626	0.817	0.734	0.845	0.872
Adjusted R^2	0.500	0.620	0.813	0.726	0.840	0.867
Residual Std. Error	0.043	0.038	0.027	0.032	0.025	0.022
F Statistic	60.506***	50.636***	177.677***	55.085***	192.936***	134.092***

Note: *p<0.1; **p<0.05; ***p<0.01

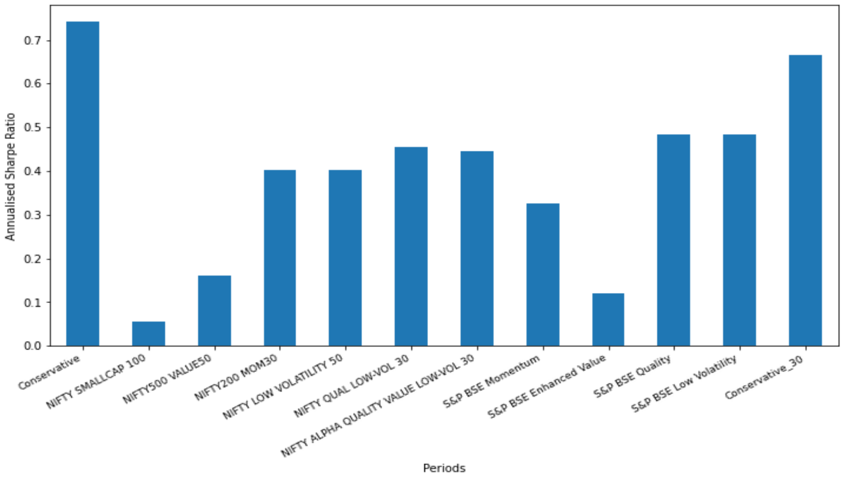
Source: Authors calculations, Raju (2022). The table shows the regression of the Conservative Minus Speculative (CMS) portfolio total returns against the returns of (1) CAPM with the Market Factor (MF), (2) 3-Factor Fama-French Model (FF3) using the MF, Size (SMB) and Value (HML), (Fama and French, 1993) (3) The 3-Factor Fama French Model plus the Momentum Factor Fama and French (1993); Carhart (1997), (4) 5-Factor Fama-French Model (FF5) with the five-factor Size (SMB), Value (HML), Op. Profitability (RMW) and Investment (CMA) (Fama and French, 2015), (5) The 5-Factor Model plus Momentum Factor (WML, and (6) Adding the self-constructed market-neutral Low-Volatility "factor" to (5). Std errors in brackets. Alpha is monthly alpha.

Figure 9: Sharpe Ratios of S&P BSE 100, Conservative and Speculative Portfolios in India across regimes, Sep 2006 - Jun 2022



Source: Authors calculations, Refinitiv Datastream, OECD India CLI. The Conservative and Speculative portfolios each consist of 100 stocks and are equally weighted and rebalanced on a quarterly frequency. For comparison we also show the S&P BSE 100 Index. All returns are total returns n excess of risk-free rates computed as annualised continuously compounded returns from start of regime period to end of regime period and are gross of costs and taxes.

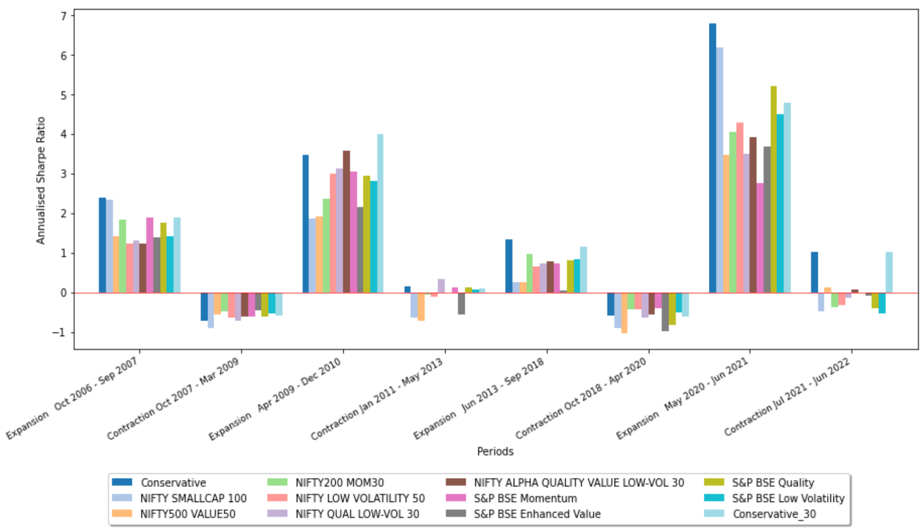
Figure 10: Sharpe Ratios of Conservative and Select single factor and multi-factor indices in India, Sep 2006 - Jun 2022



	Conservative	NIFTY SMALLCAP 100	NIFTY500 VALUE50	NIFTY200 MOM30	NIFTY LOW VOLATILITY 50	NIFTY QUAL LOW-VOL 30	NIFTY ALPHA QUALITY VALUE LOW-VOL 30	S&P BSE Momentum	S&P BSE Enhanced Value	S&P BSE Quality	S&P BSE Low Volatility	Conservative_30
Excess Return (simple)	18.3	6.9	10.7	11.6	8.8	8.6	9.2	10.0	9.1	10.6	9.7	14.6
Excess Return (compound)	16.8	1.8	5.4	9.2	7.4	7.5	7.9	7.5	3.9	9.1	8.4	13.2
Difference (simple-comp)	1.5	5.2	5.3	2.3	1.5	1.1	1.4	2.5	5.2	1.5	1.2	1.3
Std Deviation	22.6	31.6	33.7	23.0	18.3	16.5	17.7	23.0	32.8	18.8	17.4	19.9
De-risking factor (%)	100	71	67	98	123	137	127	98	69	120	129	113
Sharpe Ratio (compound)	0.74	0.06	0.16	0.4	0.4	0.46	0.44	0.33	0.12	0.48	0.48	0.66
Sharpe Ratio (simple)	0.81	0.22	0.32	0.5	0.48	0.52	0.52	0.44	0.28	0.56	0.55	0.73
Ex Return same Risk	18.3	6.8	9.3	11.5	9.4	9.5	10.0	10.0	8.3	11.4	10.6	15.7

Source: Authors calculations, Refinitiv Datastream, NIFTY Indices, S&P Dow Jones Indices. The Conservative portfolios consist of 100 (30) stocks and are equally weighted and rebalanced on a quarterly frequency. All returns are total returns over risk-free rates from the start to the end of the regime period and are gross of costs and taxes. The table has simple and compound excess returns, the chart uses continuously compounded Sharpe Ratios. Excess returns for the same risk are computed by weighting the Excess Returns (simple) by the de-risking factor and weighting the balance to the risk-free asset derisking factor to end up with the same risk as the Conservative Portfolio. So for the NIFTY SMALLCAP 100, we calculate Ex Return same Risk $= 6.9 \cdot 71 + (100 - 71) \cdot r_{rf}$ and for NIFTY LOW VOLATILITY 50 $= 8.8 \cdot 123 + (100 - 123) \cdot r_{rf}$ where r_{rf} is the annualised period risk free rate.

Figure 11: Sharpe Ratios of Conservative and Select single factor and multi-factor indices in India across regimes, Sep 2006 - Jun 2022



Source: Authors calculations, Refinitiv Datastream, NIFTY Indices, S&P Dow Jones Indices. The Conservative portfolios consist of 100 (30) stocks and are equally weighted and rebalanced on a quarterly frequency. All returns are total returns in excess of risk-free rates computed as annualised continuously compounded returns from start of regime period to end of regime period and are gross of costs and taxes.

Figure 12: One Sided Turnover of the Conservative Formula, Sep 2006 - Jun 2022

Source: Authors calculations, Refinitiv Datastream.