Risk Factors For the Indian Equity Market: Statistics, Visualization, and an Interactive Tool

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Abstract

We construct monthly time series of the six Fama–French factors for the Indian equity market. We motivate and document the protocols, filters, and weights used to build the series, distinguishing what we draw from established U.S. practice from what we adapt to the local market structure in India. In conservative value-weighted portfolios, long portfolios have annual returns of between 14% and 23% while factor premiums return between 3.4% and 10.8%. The return premiums show considerable volatility over time. All performance metrics depend materially on the universe, filters, and construction protocols, underscoring the need for care in building and interpreting factor premiums. We also introduce a suite of interactive tools and stock-level labels that let researchers and practitioners analyze the dynamics of premiums, cumulative returns, and performance for a flexible set of long-short strategies over alternative horizons.

The data and interactive tools are available at `quantfin-scdlds.com`.

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1 Introduction

The Fama–French factors have become foundational in empirical asset pricing as parsimonious representations of sources of systematic risk. The early multifactor model of Fama and French (1993) supplements the classic CAPM market factor with size and value. Subsequent work adds three factors: Carhart (1997) introduced momentum, Novy-Marx (2013) a profitability factor, and Titman, Wei and Xie (2004) and Anderson and Garcia-Feijoo (2006) an investment factor. See Fama and French (2016). The six factors are important in academic research and practice. Other factors and alternative implementations of old factors continue to emerge, resulting in what is called a factor zoo. The additional factors often face higher bars to show that they are not spanned by existing factors and to mitigate suspicions of data dredging and snooping.[1]

Factor models serve a variety of purposes. Perhaps the most important of them is that they are return benchmarks that help test whether any proposed trading strategy generates genuine alpha. Factors help decompose and attribute the style and performance of mutual fund and pension fund managers or advisors providing portfolio management services.[2] Factor premiums also serve as targets for mutual funds and ETFs that drive the large factor investing industry. In corporate finance, they serve as benchmarks to test post-announcement portfolio and calendar time returns. Factor models also improve cost of capital estimates used by managers to evaluate projects.

Understanding the factor risk premiums is also of economic interest. As an example, the value premium and its time variation have attracted a large body of research. For example, Zhang (2005) attributes it to risks due to frictions in right-sizing capital stocks and countercyclical risk premiums. Chen, Petkova and Zhang (2008) and Fama and French (2006) examine whether the value premium is robust over long time periods. Campbell, Giglio and Polk (2023) show that value booms and busts are related to news

[1] For example, Pastor and Stambaugh (2003) consider a liquidity factor, for which Liu (2006) and Amihud (2002) propose alternative metrics. Ehsani and Linnainmaa (2022) test if momentum is actually factor momentum. Harvey, Liu and Zhu (2016) and Feng, Giglio and Xiu (2020) assess the factor zoo.

[2] A question that often comes up is whether factors represent dimensions of risk or not. This issue is not critical in performance attribution in practice. Using factors to calibrate returns can be interpreted as the extent to which any detected alpha is spanned by already-known factors.

about aggregate cash flows, discount rates, and volatility.

We develop estimates of the six main Fama-French factors for the Indian equity market. India is a developing economy with 2025 GDP of about $4 trillion and stock market capitalization of $5 trillion. While relatively modest in relation to the large U.S. economy (GDP and stock market capitalization of $30 trillion and $75 trillion, respectively), the Indian stock market is extremely old and established with distinct signatures in market development, participation, regulations, and trading and in particular, a history of uninterrupted operations since 1875, when it was established as The Native Share And Stock Brokers' Association. The exchange is now called the BSE. Its operations continued past Indian independence under strict control through the Controller of Capital Issues. A major shift occurred in 1992-1994 on the heels of stock market scandals, when the National Stock Exchange (NSE) was established. A system of electronic screen-based trading was introduced at the time, a transition to which was largely completed around 2000. Our estimates of factor premiums around this time.

We are not the first to develop data on factor premiums for the Indian market. A prominent four-factor model that includes the three Fama and French (1993) factors and momentum was developed by Agarwalla, Jacob and Varma (2014) (AJV, henceforth), originally for stocks listed on the BSE and subsequently extended to NSE stocks. An ambitious effort is by Jensen, Kelly and Pedersen (2023) (JKP, henceforth), who construct 153 factors across 13 "themes" for 93 countries. The data include India. Factor construction requires the researcher to make multiple empirical choices. The differences between the studies illustrate the often-difficult choices in constructing factors and benchmarks, specifically the degree to which the factors must be standardized across markets based on (say) U.S. cutoffs versus localization that respects the distribution of size and trading volumes in individual countries.[3]

Our approach is to lay out our own factor construction choices transparently. We also provide tools to users to generate, visualize, and possibly customize and assess alternative

[3]Here, we note the distinction between stocks used to construct factor premiums and ones used in portfolio formation and trading. Realizable returns in trading strategies need significant adjustments for transaction costs due to illiquidity (Novy-Marx and Velikov, 2015).

approaches. Our preferred choices for factor estimation tilt towards more traded stocks that have more reliable return data, towards value-weights rather than equal weights (although our interactive tool provides both estimates), and based on local market structure. These are, of course, researcher choices and involve judgment. We provide resources that allow researchers to generate and analyze alternatives. Our interactive tool allows selection of the stock universe, including the top 300 or top 500 stocks by market capitalization that largely reflect what is tradable at scale, and both value and equal weights. Our ongoing efforts focus on research using the factors, on developing other ones, and estimating transaction costs to help create reliable research foundations for the Indian equity market.

The remainder of the paper is structured as follows. Section 2 describes the data and filters used to construct factors. Sections 3 and 4 detail the factor construction methodology, factor breakpoints and long-short factor formulas. Section 5 compares the results from alternative approaches towards factor construction and shows that ours tilts towards more tradable portfolios. We include here a comparison between different factor libraries for the Indian market. Section 6 briefly reviews the returns and portfolio performance of the factors. Section 7 concludes.

2 Data and Filters

Firm-level balance-sheet items, stock returns, and active trading dates come from the CMIE Prowess DX database. In the dataset, there are 7,757 unique firms with some return data between calendar 2000 and 2025. Based on our assessment of data reliability in the early years and because the momentum factor requires a year of prior returns, our factor time series begins in October 2003. We next discuss the filters we apply to generate the universe used in estimating factors.

2.1 Price Data

The Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE) are India's leading exchanges, and firms commonly cross-list on both. As of 2025, the aggregate market capitalization of BSE-listed stocks is ₹456 trillion, against ₹461 trillion on the NSE and a combined total of ₹464 trillion. The BSE lists roughly 2,000 more firms than the NSE, but these are overwhelmingly small microcaps. For cross-listed stocks, price data come from NSE where available and from BSE prices otherwise.

2.2 Accounting Data

Most Indian companies have March financial year-ends and are now required to release audited financials within 60 days. We follow the Fama-French practice of using a 6-month gap from the financial year end before using the accounting data for a year. Thus, any accounting data for the year ending on March 31 of calendar year y is used only starting from October 1 of the year and held for one year. For instance, the book value of a stock for the fiscal year ending on March 31, 2006 is applied to all months starting from October 1, 2006 to September 30, 2007.[4]

2.3 Filters

Negative Book Equity: Book equity is the total shareholder equity reported on a firm's balance sheet. We exclude firms with negative book equity when constructing the three factors that use book equity (value, profitability, and investment). These firms are retained for the size and momentum factors, which do not require book equity.[5] Figure 1 reports the annual count of negative-book-equity firms in the raw data.

[4] We note that JKP use a four-month gap. This choice is also reasonable. We choose to stay with the more conservative Fama-French choice, as there are no special local-market reasons (such as earlier filing deadlines in India relative to the U.S.) to do otherwise.

[5] As in the French data library for the U.S. market, we provide return data for negative book equity firms separately.

Penny Stock: These shares are illiquid, have noisy returns, are subject to pump-and-dump schemes, and attract less institutional interest. We define penny stocks as the ones whose median daily closing share price in the prior year is less than or equal to ₹10. We briefly comment on our empirical choice.

In the U.S., penny stock definitions come from Section 3(a)51 of the 1934 Securities and Exchange Act as amended by the 1990 Penny Stock Reform Act. We are not aware of a similar definition in India, where listing regulations specify minimum public float and market capitalization. Studies of the Indian market vary in their definitions of a penny stock. Pandey and Sehgal (2016) use a cutoff of ₹10 (roughly 10 to 20 cents), while Agarwalla, Jacob and Varma (2014) use a threshold of ₹1 (1–2 cents). A cross-country study of momentum by Jegadeesh and Titman (2023) uses a much greater cutoff of $1, which corresponds to between ₹50 and ₹90 in our sample period.

Figures 2 and 3 show that the share of firms trading below ₹10 held in a fairly narrow band, roughly 20–30% of firms, between about 2005 and 2020, and fell further thereafter as the market re-rated. Very few firms trade below ₹1. Table 1 shows that ₹10 corresponds to roughly the 25th percentile of the price distribution through about 2020, after which a market boom lifted the 25th percentile to around ₹27. On balance, the ₹10 cutoff is a stable and economically meaningful threshold for factor construction.

Microcap: The filter drops stocks with low market capitalization, which are often hard to trade in reasonable quantities. We follow Agarwalla, Jacob and Varma (2014) and define microcaps as firms whose market capitalization as of the last trading day in September of calendar year y is less than 10 percent of the median market capitalization of all stocks on this day. We apply the exclusion based on September of calendar year y from October 1 of year y to September 30 of calendar year $y + 1$. Figure 4 plots the resulting cutoff over time. It has run between roughly ₹500 crore and ₹700 crore in recent years.

Illiquidity: We term a stock illiquid between October 1 of calendar year y and September of year $y+1$ if it does not trade at least once in every full trading week in the 12-month period before September of calendar year y. This definition is more stringent than that in Agarwalla, Jacob and Varma (2014), who require trading on any 50-day period in the prior year. Our criterion filters out cases with prolonged illiquidity.

The filters are, of course, not mutually exclusive. Table 2 reports the final holding universe by portfolio year, and Table 3 the number of firms excluded each year for negative book equity.

3 Factor Construction

Our factors follow the double-sort methodology used to construct the Fama–French factors in the French data library. Stocks are sorted independently for each characteristic. We have a binary split for size at the 90th percentile – as explained below – and 30/70 tercile split for the others. Stocks are assigned labels based on these splits. The intersections of the size and characteristic sorts form the portfolios from which the long-short factors are built.

Size: We use the September end-of-month market capitalization in year y to assign the size label for the subsequent portfolio year, which is October of year y to September of year $y + 1$. Firms above the 90th percentile of market capitalization are classified as Big (B) and the rest are Small (S).

As in the U.S., the Indian market has a long tail of small firms. Table 4 shows that close to 40% of firms have a market capitalization below ₹100 crore. In the U.S., the standard remedy is to use NYSE–AMEX market capitalizations to define size breakpoints that are then applied to all firms, including those on NASDAQ. An analogous procedure would fail in Indian markets given the heavy overlap of cross-listings on the BSE and NSE. In fact, the BSE, the analog of NYSE–AMEX, lists *more* firms and more small firms, than the NSE. We define large firms as those in the top decile of market capitalization across all firms. These firms account for about 90% of total market capitalization in 2025, against roughly 78% for the top decile in the U.S. Figure 5 plots market capitalization by percentile. The mean tracks the 90th percentile of size, reflecting the right skew of the distribution of market capitalization.

Book-to-Market (B/M): The book-to-market ratio B/M is a signal of a value stock. High book-to-market stocks are value stocks, while low book-to-market indicates growth stocks whose valuation comes less from assets-in-place than from growth opportunities.

We compute B/M as the ratio of book equity in March of calendar year y to the market value of equity as of the last trading day in September of calendar year y. Firms with B/M ratio above the 70th percentile are classified as Value (V), firms below the 30th percentile are classified as Growth (G), and the remaining are Neutral (N). Firms with negative or missing book equity are excluded from value breakpoint construction and holding universe. We apply the label derived in September of calendar year y for October of year y through September of year $y + 1$.

Operating Profitability: Operating profitability is a firm's profit divided by its book equity. The numerator is sales minus cost of goods sold (COGS), selling and distribution expenses, and interest expenses. The denominator is the book value of equity. Firms above the 70th percentile of the profitability ratio are classified as Robust (R), while firms below the 30th percentile are classified as Weak (W) and the rest are Neutral (N). Both profits and book value are estimated as of year y, and the label applied for all months from October of year y to September of year $y + 1$. We exclude firms with negative book values.

Investment: The investment factor captures a firm's asset growth. Firms with high asset growth invest aggressively and are labeled Aggressive (A) while those with low asset growth are labeled Conservative (C). Following Fama and French, we measure investment as the change in total assets from the end of March of calendar year $y - 1$ to the end of March of calendar year y, scaled by assets at calendar $y-1$. We derive labels based on 70/30 cut points and apply this label for all months from October of year y through September of year $y+1$.

Momentum: We define momentum as the cumulative gross return over an 11-month formation window excluding the most recent month. Thus, for example, momentum for the month of September 2013 would include cumulative 11-month returns ending on July 31, 2013. The momentum signal is the cumulative gross return over months $t-12$ through $t-2$, the geometric product of one plus the return over the time period.

A firm must have valid returns for 11 months for the signal to be computed. Firms occasionally have missing returns for some months, the by-product of gaps in the daily return sequences that are used to produce monthly returns. Breakpoints are computed monthly at the 30th and 70th percentiles of the cross-sectional distribution of the momentum signals. Firms above the 70th percentile are assigned to the label Winner (W) and firms below the 30th percentile are classified as Loser (L). The remaining firms are assigned the label Neutral (N). For intersections of momentum and market capitalization or size, we use the equity market value as of end of the momentum period (rather than the lagged capitalization as of March 31).

Risk-Free Rate The risk-free rate is the 91-day Treasury bill rate published on the Reserve Bank of India website.

Market Factor: We define the market factor as the return on the NIFTY 500 Total Return Index (TRI)—a broad market portfolio—in excess of the risk-free rate, where the monthly risk-free rate is the 91-day Treasury bill rate at the start of the month divided by 12.

4 Factor Cut Points and Returns

All factor portfolios except momentum are constructed from annual labels assigned as of the last trading day in September of the calendar year; the label is held constant from October until the next September. Momentum is relabeled every month. We provide labels at three levels: the holding universe of all stocks that pass our filters, the top 300 stocks, and the top 500 stocks by market capitalization as of the last trading day in September.

With firms classified into two buckets based on a 90/10 split by market capitalization and the remaining characteristics split by 70/30 tercile, we have six groups. So each stock carries a size label Big (B) or Small (S) and a tercile label (Low, Neutral, or High), one per factor. Intersecting the size labels with the tercile labels yields six value-weighted portfolios for each factor: $\{S, B\} \times \{F_L, F_N, F_H\}$.

With independent sorts, a familiar empirical issue is that not all characteristic intersections are well-populated. If the number of stocks in a bucket is less than five, we use coarser definitions to construct portfolio returns, as explained below. In India, the sparsely populated cell is, perhaps surprisingly, big-value firms. This point is also noted by AJV for historical data, although we note that with the passage of time, this has not been an issue in the last decade. Thus, let n_{BV} denote the number of big-value firms and $\mathbb{1}_{NBV5}$ an indicator for whether this number exceeds five.

Size Factor (SMB): The size factor (Small-Minus-Big) is the average return of the three small portfolios minus the average return of the three big portfolios:

$$\text{SMB} = \frac{1}{3}\big[(SV - BV) + (SN - BN) + (SG - BG)\big] \text{ if } \mathbb{1}_{NBV5} = 1, \tag{1}$$

where SV, SN, SG denote the Small-Value, Small-Neutral, and Small-Growth portfolios, respectively, and BV, BN, BG denote their Big counterparts.

If BV has fewer than five firms, we drop the BV and SV portfolios, and SMB is computed using only the neutral and growth pairs.

$$\text{SMB} = \frac{1}{2}\big[(SN - BN) + (SG - BG)\big] \text{ if } \mathbb{1}_{NBV5} = 0 \tag{2}$$

Value Factor (HML): The value factor (High-Minus-Low book-to-market) is the average return of the two value portfolios minus the average return of the two growth portfolios:

$$\text{HML} = \frac{1}{2}\big[(SV - SG) + (BV - BG)\big] \text{ if } \mathbb{1}_{NBV5} = 1 \tag{3}$$

The long portfolios are Small-Value and Big-Value and the short ones are Small-Growth and Big-Growth. When $n_{BV} < 5$, HML is essentially the difference between small value and small growth:

$$\text{HML} = SV - SG \text{ if } \mathbb{1}_{NBV5} = 0, \tag{4}$$

Momentum Factor (WML): The momentum factor (Winner-Minus-Loser) is the average return of the two winner portfolios minus the average return of the two loser portfolios:

$$\text{WML} = \frac{1}{2}\big[(SW - SL) + (BW - BL)\big], \tag{5}$$

where SW and BW denote the Small-Winner and Big-Winner portfolios, and SL and BL denote the Small-Loser and Big-Loser portfolios.

Operating Profitability Factor (RMW): It is the difference between the average return of the two robust portfolios and the average return of the two weak portfolios:

$$\text{RMW} = \frac{1}{2}\big[(SR - SW) + (BR - BW)\big], \tag{6}$$

where SR and BR denote the Small-Robust and Big-Robust portfolios and SW and BW denote the Small-Weak and Big-Weak portfolios.

Investment Factor (CMA): The investment factor (Conservative-Minus-Aggressive) is the average return of the two conservative portfolios minus the average return of the two aggressive portfolios:

$$\text{CMA} = \frac{1}{2}\big[(SC - SA) + (BC - BA)\big], \tag{7}$$

where SC and BC denote the Small-Conservative and Big-Conservative portfolios, and SA and BA denote the Small-Aggressive and Big-Aggressive portfolios.

See Table 5 for a summary of factor construction: Panel A gives the long and short legs, and Panel B the breakpoints and labels.

5 Comparisons

We compare our samples with those from AJV (Agarwalla, Jacob and Varma, 2014) and JKP (Jensen, Kelly and Pedersen, 2023). AJV study Indian equities while the JKP India sample is a subset of their global dataset covering 93 countries. We compare the three datasets. The basic thrust of the comparison is that our portfolios tilt towards larger, more liquid equities.

Comparison with AJV: Our microcap and negative book equity filters are essentially identical to those in Agarwalla, Jacob and Varma (2014). A relatively minor difference is the selection of the price series. We use the NSE where available and otherwise the BSE price, while they select the price in the exchange with greater liquidity. We do not know the exact liquidity measure (e.g., volume, turnover, bid-ask spread, depth, or nature of limit order book) but filters for traded value and quantity yield similar results. This is not surprising as with automated trading, the low-hanging fruit of inter-exchange arbitrage is likely eliminated. Our other filters differ. Our liquidity filter requires trading at least once a week over a year, while AJV specify any 50-day window. Our rule eliminates equities whose trading is lumpy or clustered, which would be admitted under the 50-day rule but do not feature in our sample. The penny stock threshold is ₹10, based on the median price over the preceding portfolio year, against ₹1 in AJV.

Table 6 and Figure 6 report the number of firms in our universe, the AJV universe, and the full CMIE Prowess base for each year. Our filters are markedly stricter in the early years. For instance, in 2000 we retain 858 firms against 2,027 for AJV, out of a base of 3,539 firms. The gaps narrow over time, especially in the most recent years. A natural question is what kinds of stocks are eliminated by our stricter filters. Figure 7 reports total September-end market capitalization for the AJV universe, our universe, and the excluded firms, by year. Excluded firms account for 0.6–8.0% of total market capitalization, with early peaks around 2002 and 2006, and stay at or below 2.1% from 2013 onward. Trading volume tells the same story. Excluded firms are under 10% of annual volume at their peak and typically 1–3% of the total after 2013 (Figure 8). The firms we drop are relatively marginal contributors to market cap and trading volume.

Figure 9 reports median market capitalization for the two universes and for excluded firms. The excluded firms' median is close to 10% of our universe's throughout the sample period. This is, of course, the microcap threshold itself, a further indication confirming that the filter operates as intended. In absolute terms the excluded median stays small, on the order of a few tens of crore, peaking at ₹90 crore in recent years as overall market levels rose.

Comparison with JKP: The Jensen, Kelly and Pedersen (2023) global factor data are constructed using CRSP, COMPUSTAT, and COMPUSTAT Global databases and inherit their identifiers and characteristics. Their monthly portfolios are based on tercile cutoffs for each country's non-microcap stocks. These are defined using a U.S. standard, as firms whose market equity converted at current exchange rates is above the NYSE 20th percentile. In addition to equal weights and value weights, they propose a capped value weight in which value weights cannot exceed the weight of the 80th percentile firm among all NYSE lists.

Our data use local market based cutoffs rather than ones based on U.S. data. A key issue with matching datasets is the absence of common identifiers between CMIE Prowess and their dataset. We attempted to map the two using a multi-stage fuzzy name-matching procedure. The first level included cleaned full names after removing generic suffixes such as *Ltd.* and *Industries.* The second-level match uses two- and three-token name prefixes and the last step uses spaceless normalized names to handle spelling variants. A relatively small number of 113 firms remain unmatched.

Table 6 and Figure 10 compare firm counts in our universe and the JKP universe by year. After 2012 the JKP universe contains close to twice as many firms as ours. The gap is almost entirely attributable to our filters. Since 2013, over 95% of the firms that appear only in JKP fail at least one of them, as Figure 11 shows. The standardized global filter they use appears to include firms that our local market filters remove. The unexplained residual comprises about 54 to 66 firms per year, the pool of 113 firms we could not match between the CMIE and WRDS identifiers. The characteristics of JKP-only firms reinforce the case for our exclusions. Figure 12 shows that their median price is ₹12, against ₹87 for our universe; Table 7 shows they trade a median of 178 days per year, against 248 for ours; and Figure 13 shows their median market capitalization stays well below ours throughout. In short, the JKP-only firms are cheaper, less liquid, and smaller, which our filters (and those in AJV) remove.

Taken together, our exclusions drop firms that are small, illiquid, and priced below the penny threshold, firms whose return measurement is least reliable and represent under 2% of total market capitalization and under 3% of trading volume in the post-2013 period.

6 Returns

6.1 Long-Only Portfolios

Table 8 reports the performance of the long legs of the six factors over the full sample, October 2003 to May 2026. All six earn high returns. Momentum (Winner) is the strongest, compounding at 22.82% per year with the highest Sharpe ratio, 0.70. Value and size follow on raw return, at 20.25% and 19.68% per year (Sharpe ratios of 0.53 and 0.54). Profitability and investment are the weakest legs, compounding at 15.07% and 14.38% per year (Sharpe ratios of 0.45 and 0.41). These two factors are marginally outperformed by Nifty500 TRI benchmark on raw return, which compounds at 15.52% with a Sharpe ratio of 0.48. These returns come with large drawdowns, between −61% and −72%, reflecting the high volatility of concentrated, value-weighted portfolios. Because the legs are long positions, their Sharpe ratios are computed on returns in excess of the risk-free rate. An equal-weighted combination of the five legs compounds at 18.76% per year with a Sharpe ratio of 0.55 (final row of the table); dropping momentum from the combination barely changes it (Sharpe 0.51), because the long-only legs all carry heavy common market exposure. Figure 14 plots cumulative wealth, with the risk-free rate shown for reference.

6.2 Long-Short Portfolios

Table 9 reports the long-short factor premiums over the same sample. All five are positive. Momentum is again the strongest, compounding at 10.81% per year (12.62% in arithmetic mean) with a Sharpe ratio of 0.61. The value premium follows at 4.19% per year (Sharpe 0.32), and the size, profitability, and investment premiums are more modest, between 3.35% and 3.87% per year, with Sharpe ratios of 0.33 to 0.48. Because a long-short factor is self-financing, its Sharpe ratio is the raw mean return divided by volatility, with no risk-free adjustment. Drawdowns range from −20% for investment to −69% for value. Because the five premiums are nearly uncorrelated (average pairwise correlation −0.03), an equal-weighted combination is far more efficient than any single factor: it earns 6.09% per year at only 5.96% volatility, a Sharpe ratio of 1.02—well above momentum's 0.61 (final row of the table). Momentum carries high volatility, so one might expect little benefit from including it; yet because its return is high and it is uncorrelated with the others, dropping it lowers the combination's Sharpe markedly, to 0.78. The intuition that a single factor's own volatility matters little applies only in large portfolios; with five factors, momentum's contribution remains pronounced. Figure 15 plots cumulative wealth, with the risk-free rate shown for reference.

Our preferred construction value-weights stocks within each leg; the interactive tool also offers equal weights. Because equal weighting overweights the smallest, least tradable stocks and produces long-only returns we view as illustrative rather than achievable, we report those results, and our reasons for treating value weighting as the conservative and tradable benchmark, in Appendix A.

6.3 Market Betas and Crashes

Table 10 reports market betas estimated over non-overlapping five-year windows. The long-only legs carry full market exposure, with betas near or above one. The long-short factors are close to market-neutral, with betas mostly between -0.4 and 0.6; momentum in particular has a negative market beta in most windows, consistent with its tendency to underperform in sharp market rebounds.

Figure 16 marks the months in which a series lost more than 20%—a "crash" in the quant vernacular. Among the factors, only the market and momentum ever crash: the market in October 2008 and March 2020, and momentum in December 2008, May 2009 (-38%), and January 2012. The size, value, profitability, and investment premiums never suffer a monthly crash. Notably, momentum's crashes do not coincide with the market's—they fall in sharp rebounds—which is part of why the combination above benefits from momentum despite its volatility. The long-only legs, by contrast, crash together with the market in 2008 and 2020.

We now compare our factor premiums against the series published by AJV and JKP. Table 11 reports statistics for all three over their common window, October 2003 to March 2023. The methodologies agree on the broad ranking—momentum is the strongest premium, and profitability and investment the most stable—but differ markedly in levels. AJV produce the largest value and momentum premiums (9.4% and 13.8% per year, with Sharpe ratios of 0.59 and 0.74), reflecting their broader, less filtered universe, which retains more of the small and illiquid stocks that carry higher premia; their size premium, however, is slightly negative. JKP sit at the other extreme: their value and momentum premiums are close to zero (0.2% and 0.5%), and their profitability and investment factors, while positive, are far more volatile than ours (volatilities near 15% against 9–11%). Our premiums lie in between, with the highest risk-adjusted profitability factor (Sharpe 0.57) and a momentum premium (10.1%, Sharpe 0.56) that trails only AJV's. The pattern is consistent with the universe choices documented above: our filters trade away some premium for tradability.

Momentum is the common thread across all of these results. It earns the highest long-only return and Sharpe ratio, the largest long-short premium, and a positive premium in every one of the three libraries—the most reliable source of returns in the Indian market over our sample.

7 Conclusion

We have constructed a comprehensive factor library for the Indian equity market spanning close to 25 years. Beyond the standard Fama–French and momentum factors, we provide additional factors and tools that should be useful to both practitioners and researchers. We compare our construction in detail against the existing Indian libraries, drawing on their strengths while adapting the methodology to local market structure. In ongoing work, we use these factors to address further questions in Indian asset pricing. Among the factors, momentum stands out: across our portfolios and across all three Indian libraries, it delivers the highest returns and the strongest risk-adjusted performance over the sample.

References

Agarwalla, Sobhesh Kumar, Joshy Jacob, and Jayanth R Varma. 2014. "Four Factor Model in Indian Equities Market." Indian Institute of Management Ahmedabad Working Paper W.P. No. 2013-09.

Amihud, Yakov. 2002. "Illiquidity and Stock Returns: Cross-Section and Time-Series Effects." *Journal of Financial Markets*, 5(1): 31–56.

Anderson, Christopher, and Luis Garcia-Feijoo. 2006. "Empirical Evidence on Capital Investment, Growth Options, and Security Returns." *Journal of Finance*, 61(1): 171–194.

Campbell, John, Stefano Giglio, and Christopher Polk. 2023. "What Drives Booms and Busts in Value." *NBER Working Paper 31589.*

Carhart, Mark M. 1997. "On persistence in mutual fund performance." *The Journal of finance*, 52(1): 57–82.

Chen, Long, Ralitsa Petkova, and Lu Zhang. 2008. "The expected value premium." *Journal of Financial Economics*, 87(2): 269–280.

Ehsani, Sina, and Juhani Linnainmaa. 2022. "Factor Momentum and the Momentum Factor." *Journal of Finance*, 77(3): 1877–1919.

Fama, Eugene, and Kenneth French. 2006. "The Value Premium and the CAPM." *Journal of Finance*, 61(5): 2163–2185.

Fama, Eugene F, and Kenneth R French. 1993. "Common risk factors in the returns on stocks and bonds." *Journal of financial economics*, 33(1): 3–56.

Fama, Eugene F, and Kenneth R French. 2016. "Dissecting anomalies with a five-factor model." *The Review of Financial Studies*, 29(1): 69–103.

Feng, Guanhao, Stefano Giglio, and Dacheng Xiu. 2020. "Taming the Factor Zoo: A Test of New Factors." *Journal of Finance*, 75(3): 1327–1370.

Harvey, Campbell, Yan Liu, and Heqing Zhu. 2016. "... and the Cross-section of Rxpected Returns." *Review of Financial Studies*, 29: 5–68.

Jegadeesh, Narasimhan, and Sheridan Titman. 2023. "Momentum: Evidence and insights 30 years later." *Pacific-Basin Finance Journal*, 82: 102202.

Jensen, Theis Ingerslev, Bryan Kelly, and Lasse Heje Pedersen. 2023. "Is There a Replication Crisis in Finance?" *The Journal of Finance*, 78(5): 2465–2518.

Liu, Weimin. 2006. "A Liquidity-Augmented Capital Asset Pricing Model." *Journal of Financial Economics*, 82(3): 631–671.

Novy-Marx, Robert. 2013. "The other side of value: the gross profitability premium." *Journal of Financial Economics*, 108(1): 1–28.

Novy-Marx, Robert, and Mihail Velikov. 2015. "A Taxonomy of Anomalies and Their Trading Costs." *Review of Financial Studies*, 29(1): 104–147.

Pandey, Asheesh, and Sanjay Sehgal. 2016. "Explaining size effect for Indian stock market." *Asia-Pacific Financial Markets*, 23(1): 45–68.

Pastor, Lubos, and Robert Stambaugh. 2003. "Liquidity Risk and Expected Stock Returns." *Journal of Political Economy*, 111(3): 642–683.

Titman, Sheridan, K. Wei, and F. Xie. 2004. "Capital investments and stock returns." *Journal of Financial and Quantitative Analysis*, 39(4): 677–700.

Zhang, Lu. 2005. "The Value Premium." *Journal of Finance*, 60(1): 67–103.

Figure 1: Count of firms with negative book equity at portfolio formation, by year.

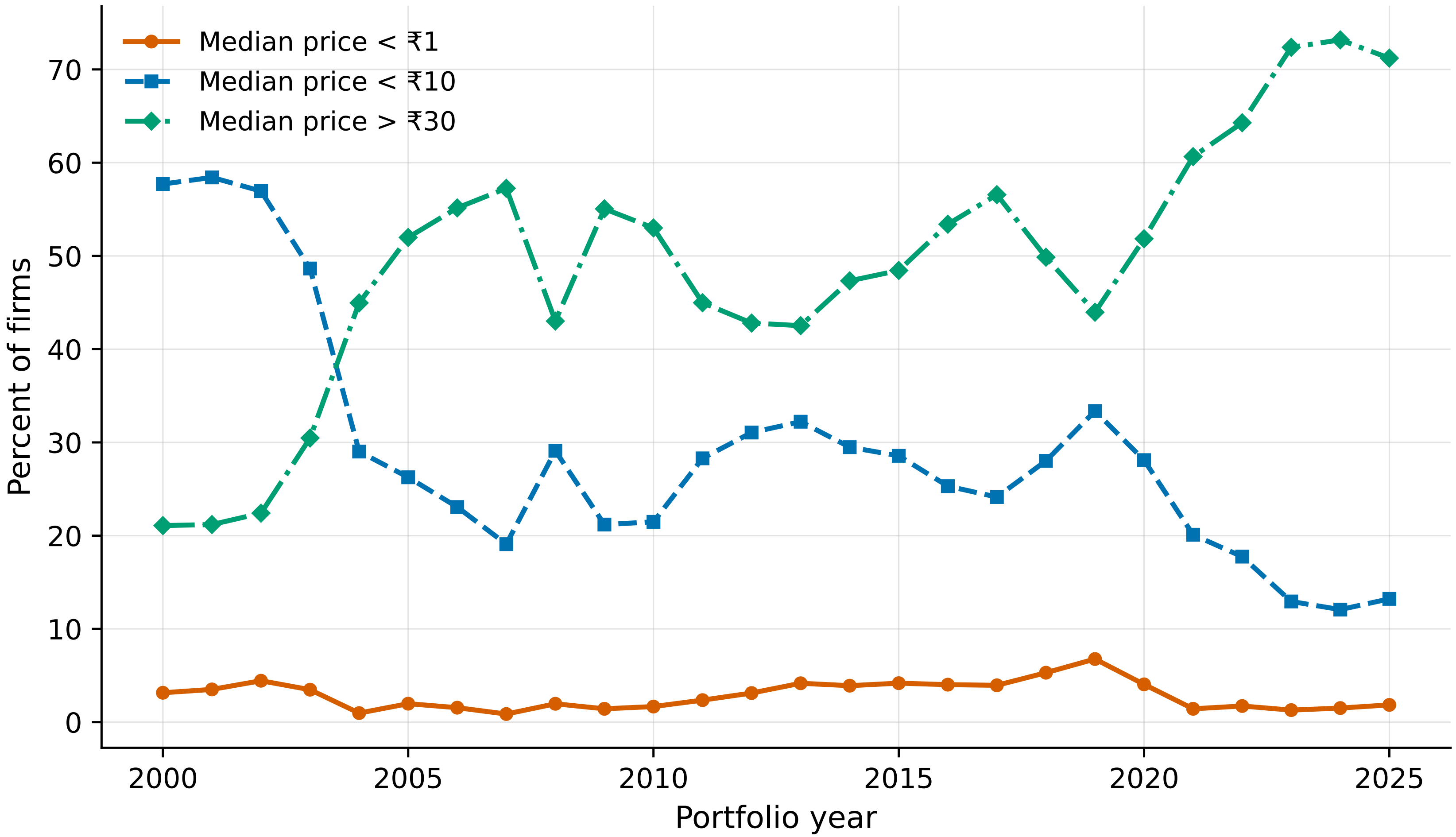

Figure 2: Share of firms below price thresholds, by year. Each line is the percentage of firms whose median annual price is below ₹1, below ₹10, or above ₹30.

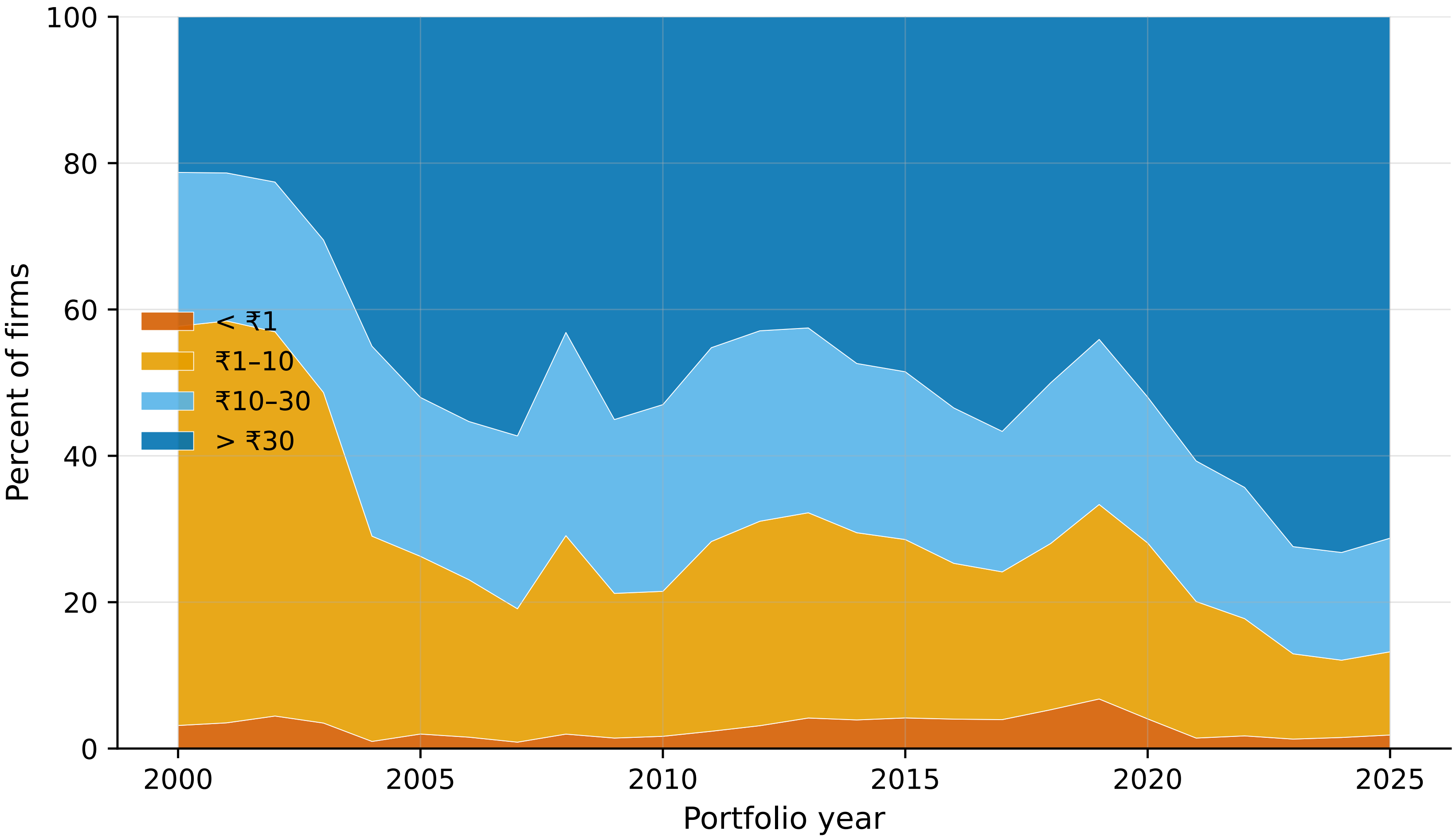

Figure 3: Composition of firms across share-price buckets, by year. Bars show the percentage of firms in each median-annual-price bucket.

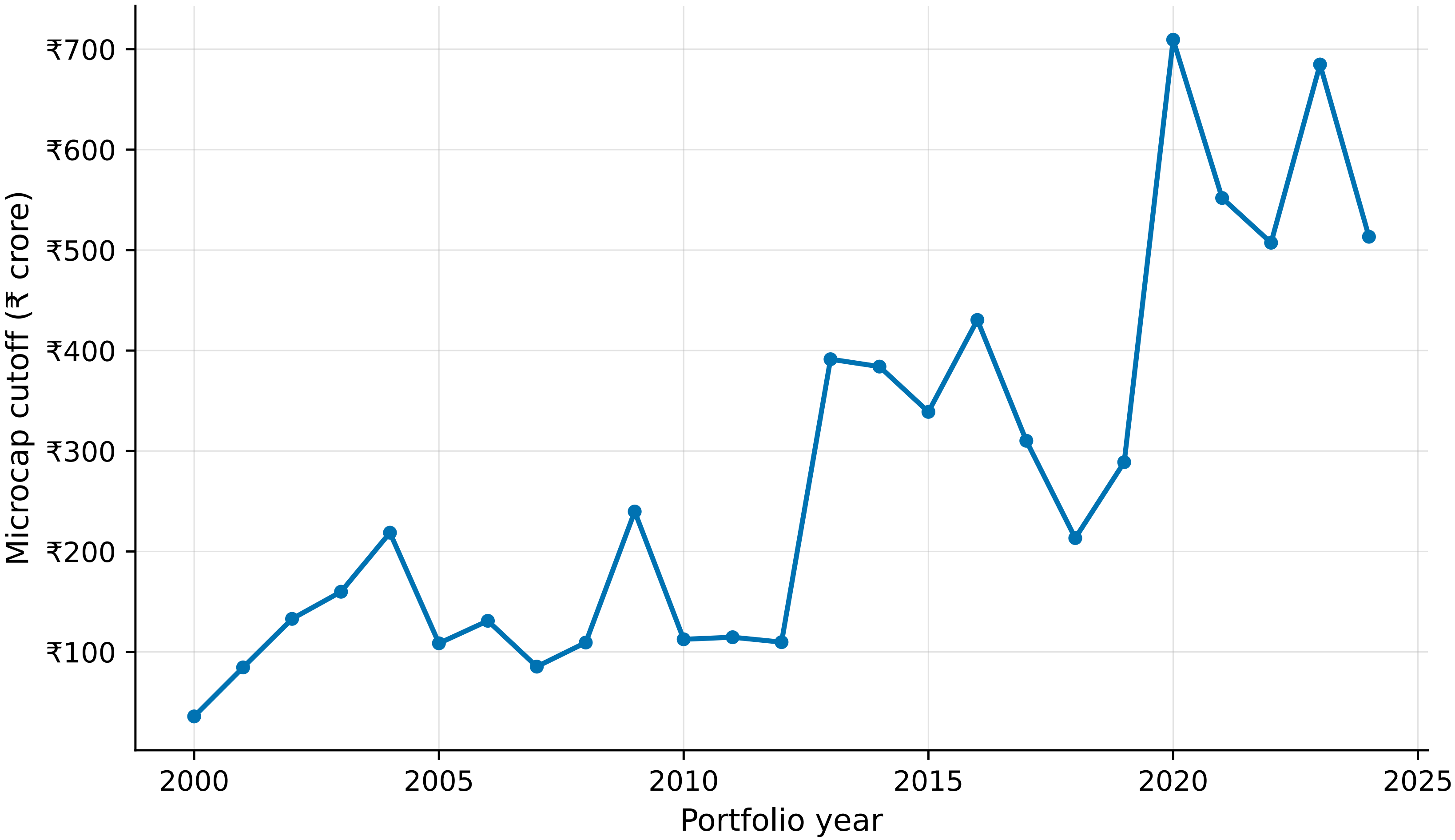

Figure 4: Microcap size cutoff, by year, in ₹crore. The cutoff is the market value of equity below which a firm is classified as microcap, set at ten percent of the median market capitalization.

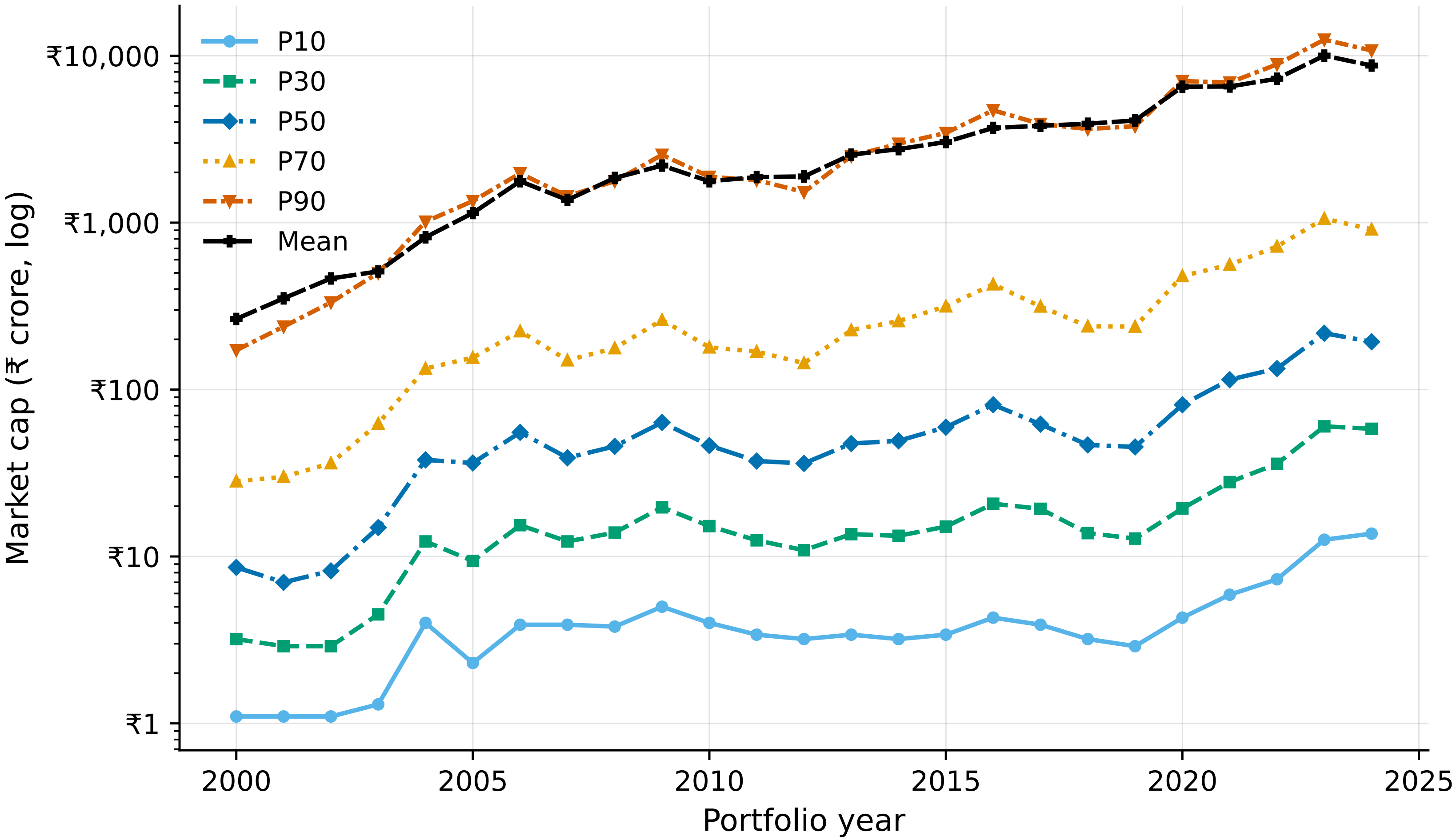

Figure 5: Market capitalization across percentiles of the firm-size distribution, by year (₹crore, log scale).

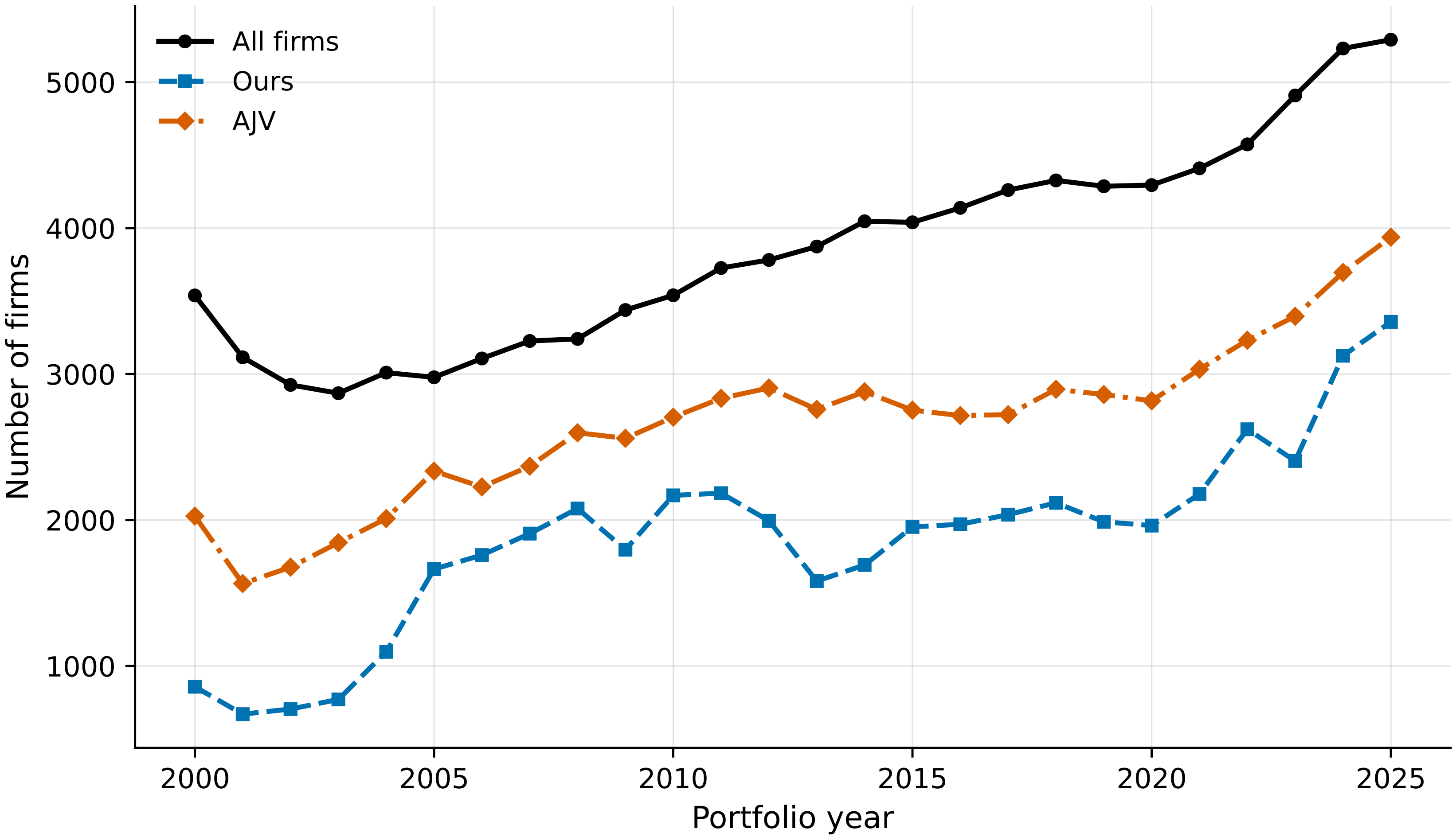

Figure 6: Firm counts by year. Bars show our universe and the AJV universe; the dotted line is the total CMIE Prowess base.

Figure 7: Total September-end market capitalization for our universe, the AJV universe, and excluded firms (left axis, ₹crore, log scale), and the share of market capitalization excluded by our filters (right axis).

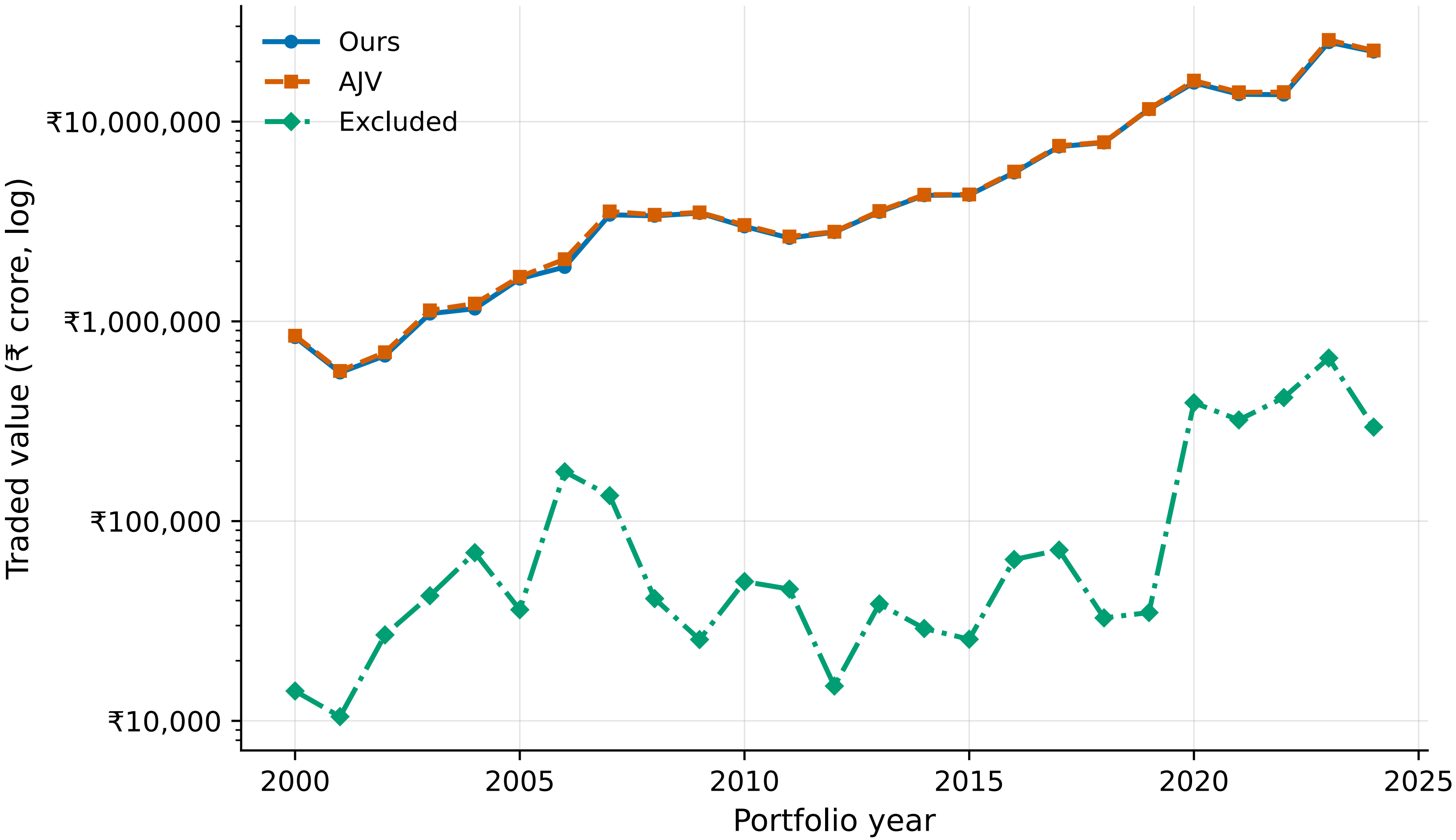

Figure 8: Total annual trading value for our universe, the AJV universe, and excluded firms (left axis, ₹crore, log scale), and the share of volume excluded by our filters (right axis).

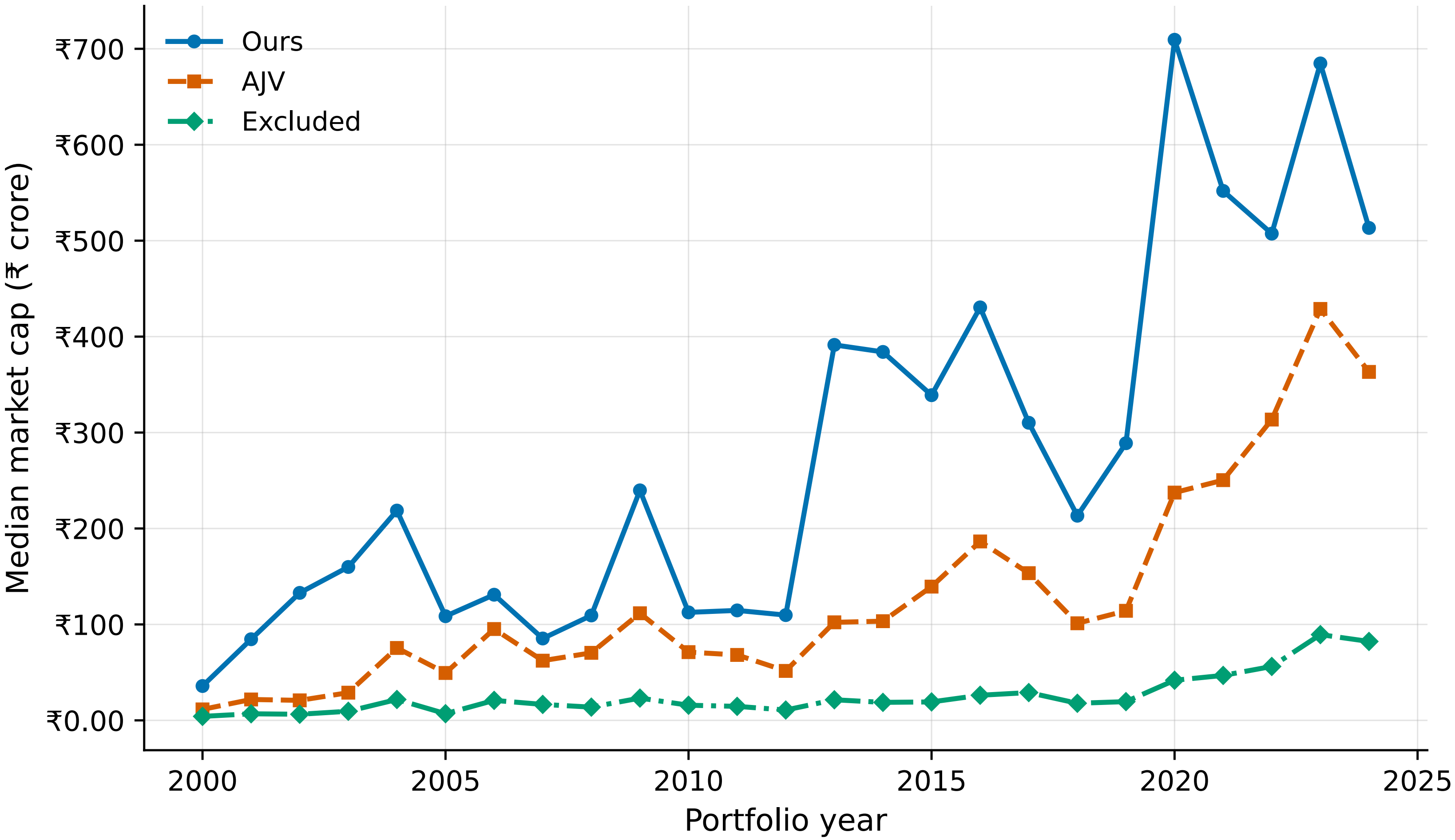

Figure 9: Median market capitalization by year for our universe, the AJV universe, and excluded firms (₹crore, log scale). Excluded firms are those dropped by the penny-stock, microcap, and illiquidity filters.

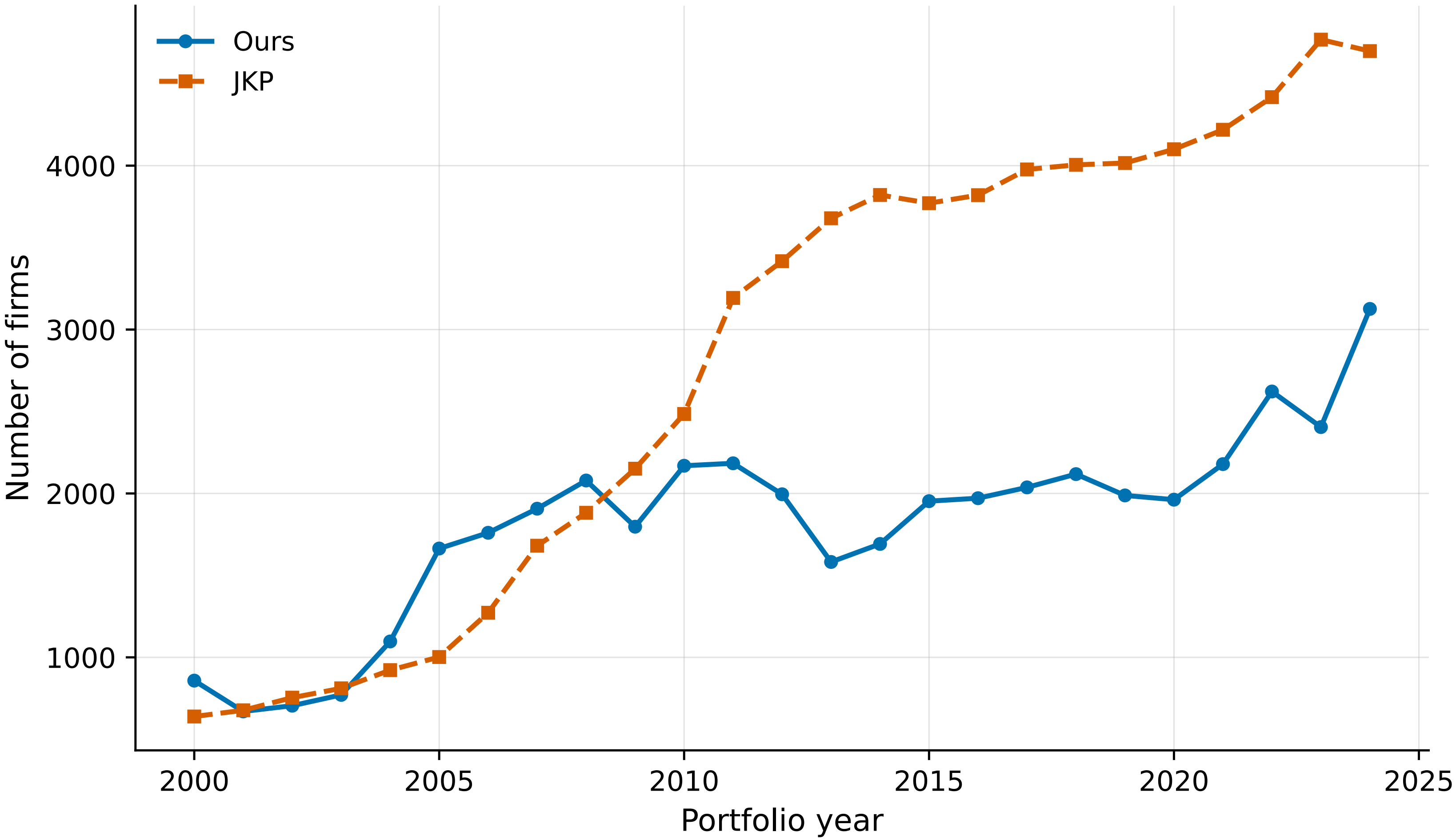

Figure 10: Firm counts by year for our universe and the JKP universe.

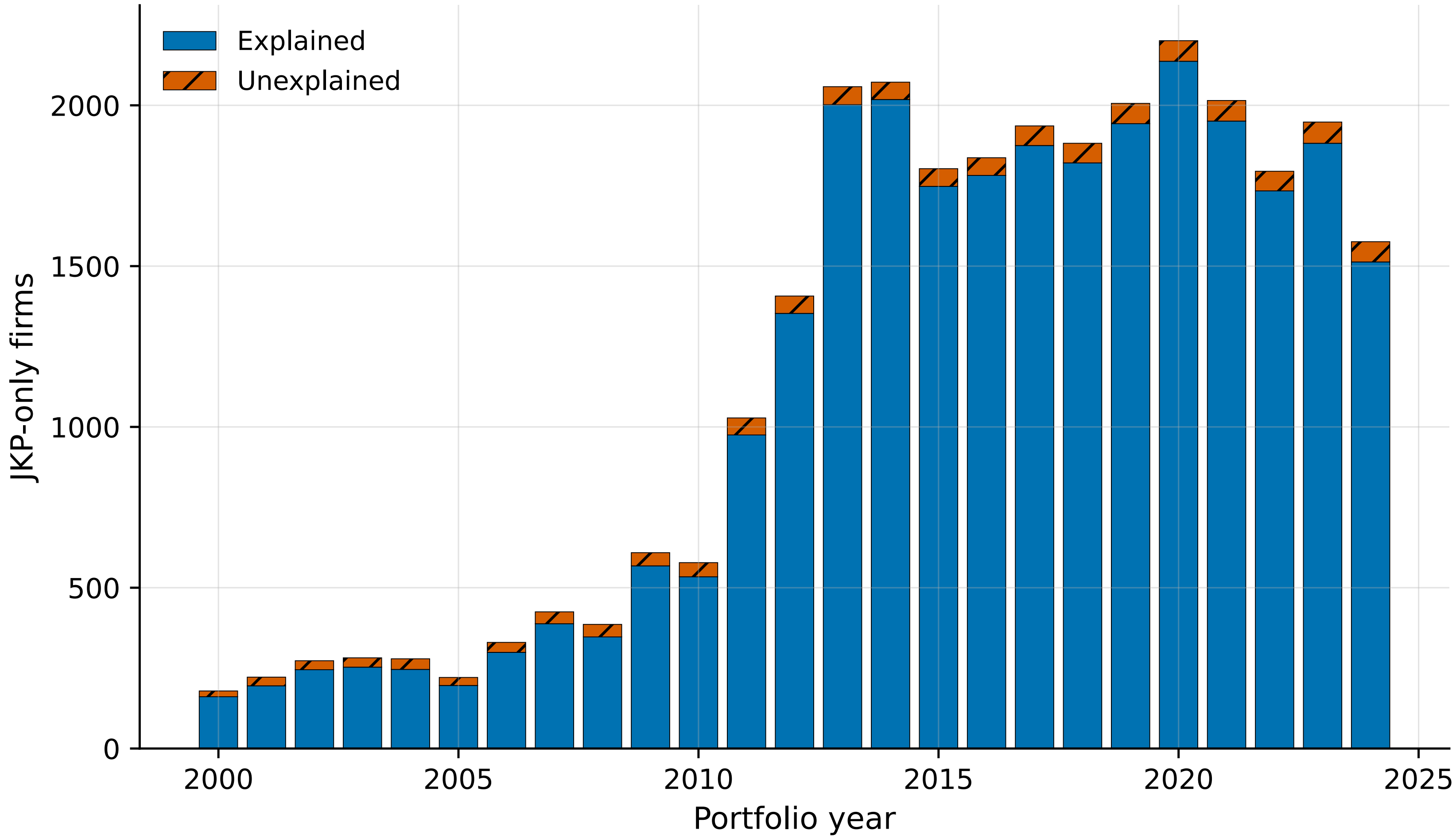

Figure 11: Decomposition of JKP-only firms by year. Bars show firms excluded by our filters (explained) and firms that could not be matched across the CMIE and JKP identifiers (unmatched).

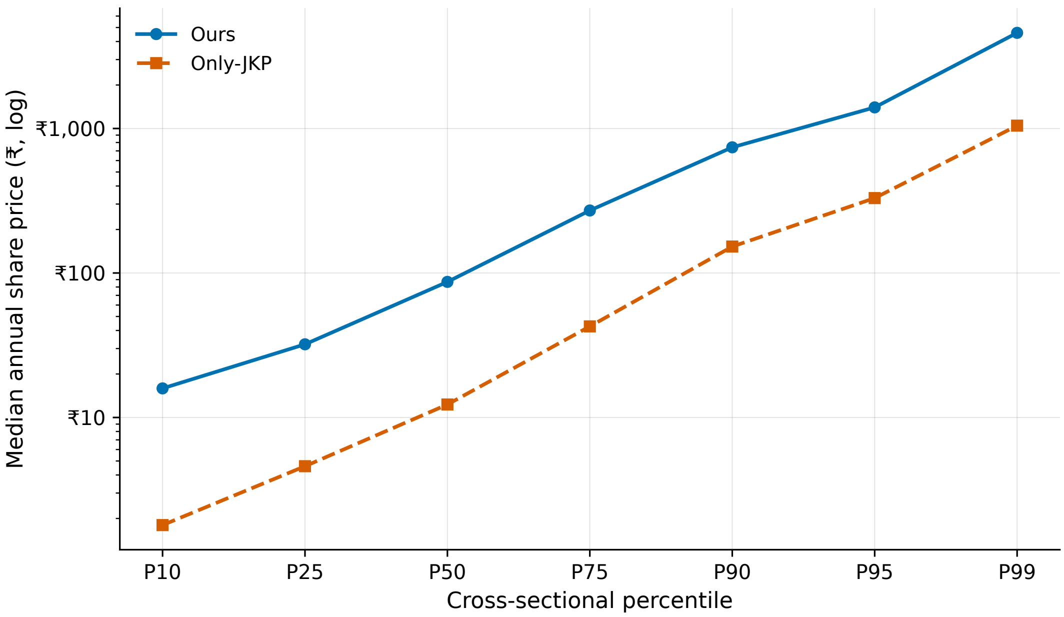

Figure 12: Cross-sectional distribution of firm-level median annual share price, for our holding universe and for firms that appear only in the JKP universe, plotted across percentiles of the price distribution (₹, log scale). Prices are measured as of the last trading day of September.

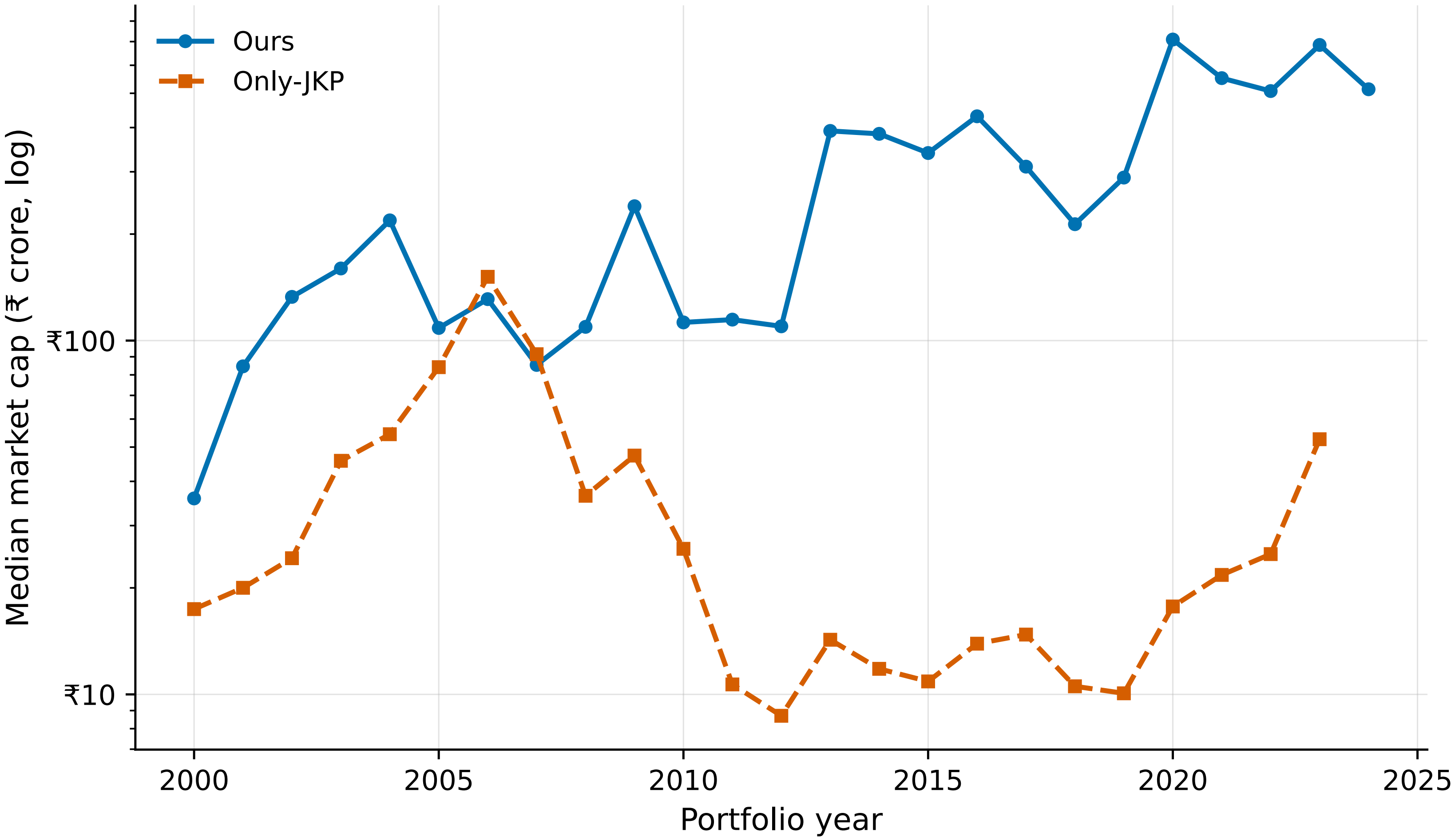

Figure 13: Median market capitalization by year for our universe and for JKP-only firms (₹crore, log scale).

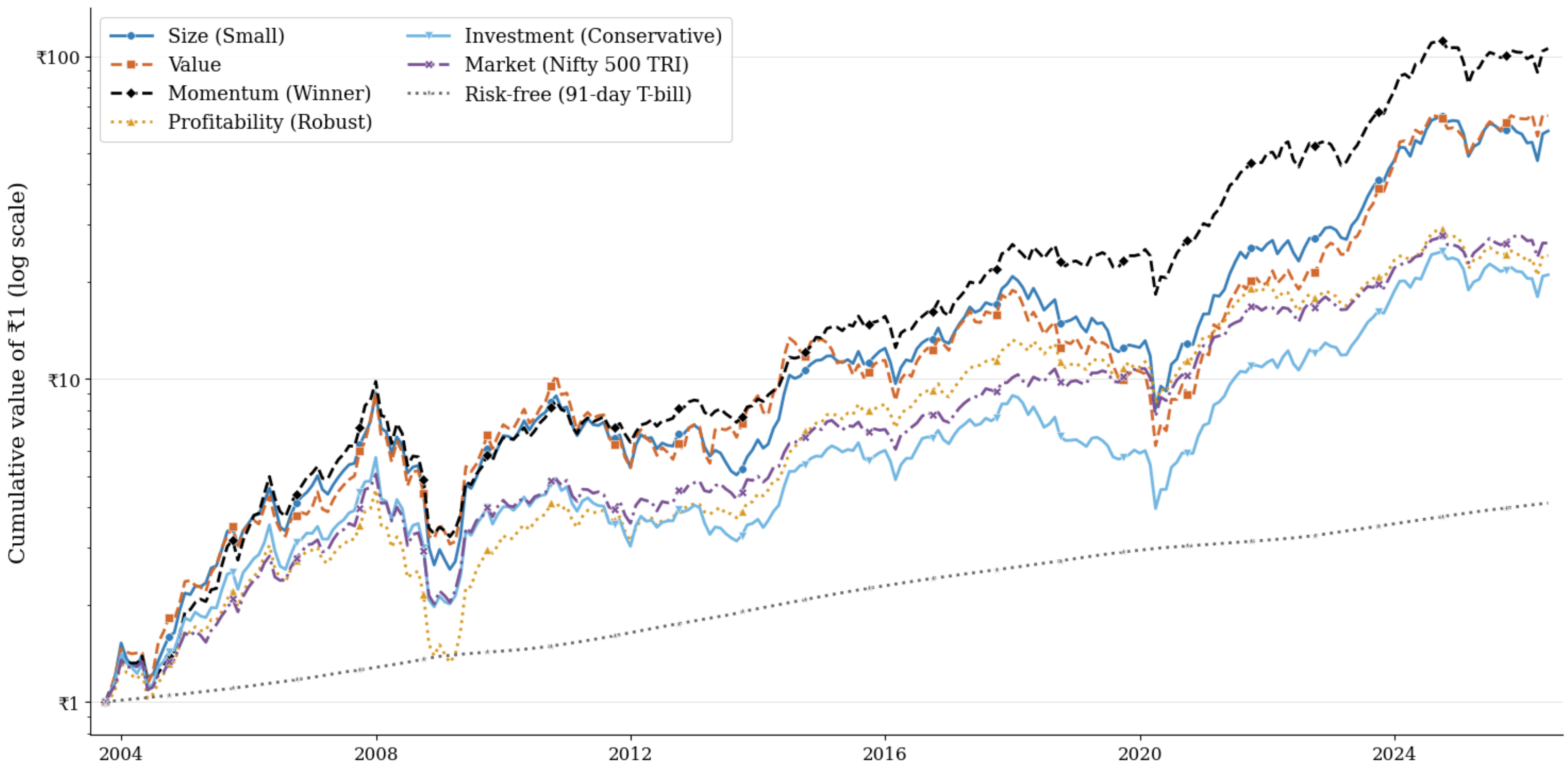

Figure 14: Cumulative value of ₹1 invested in each long-only, value-weighted factor portfolio, October 2003 to May 2026 (log scale).

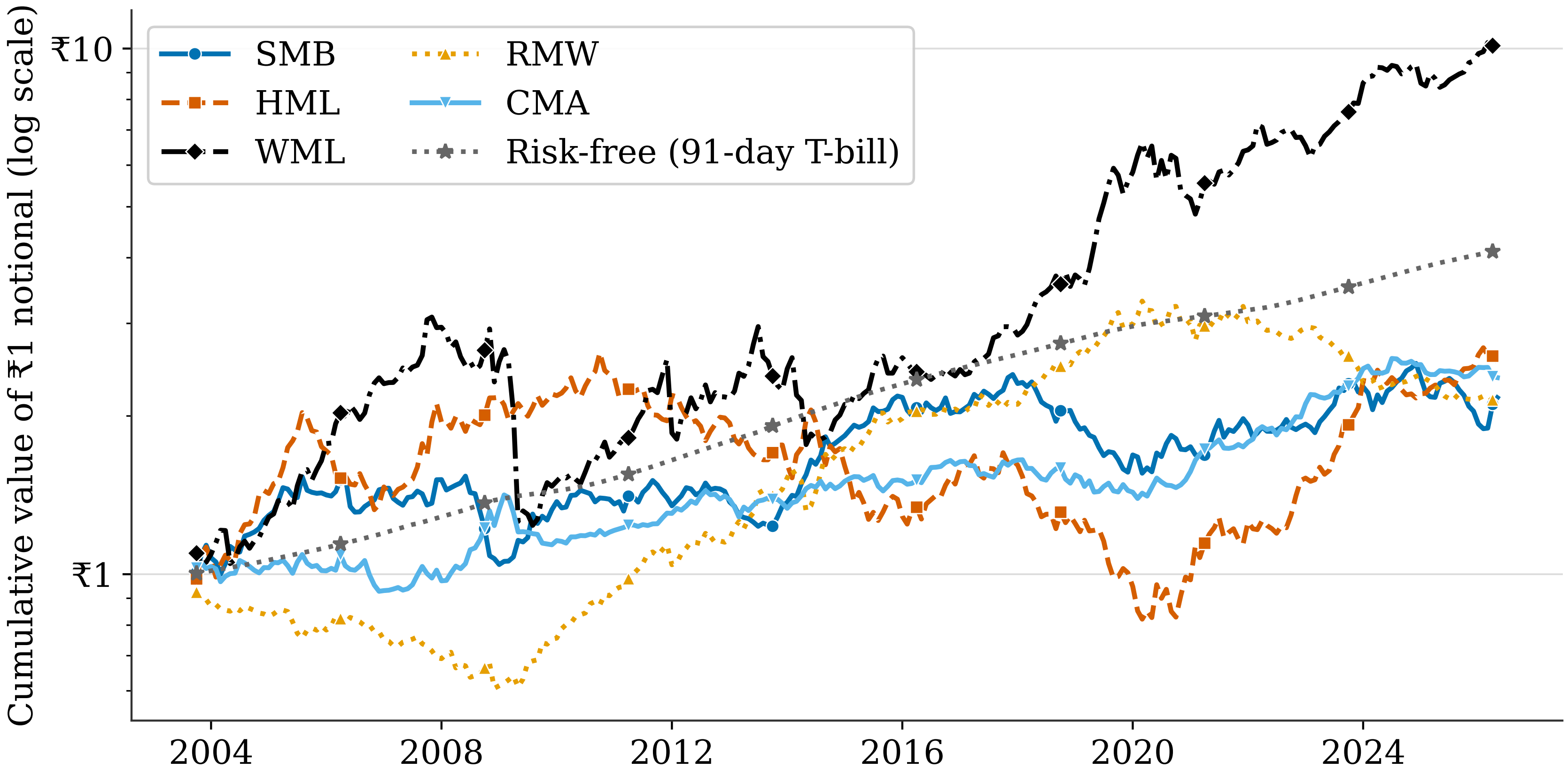

Figure 15: Cumulative value of ₹1 of notional exposure in each long-short, value-weighted factor portfolio, October 2003 to May 2026 (log scale).

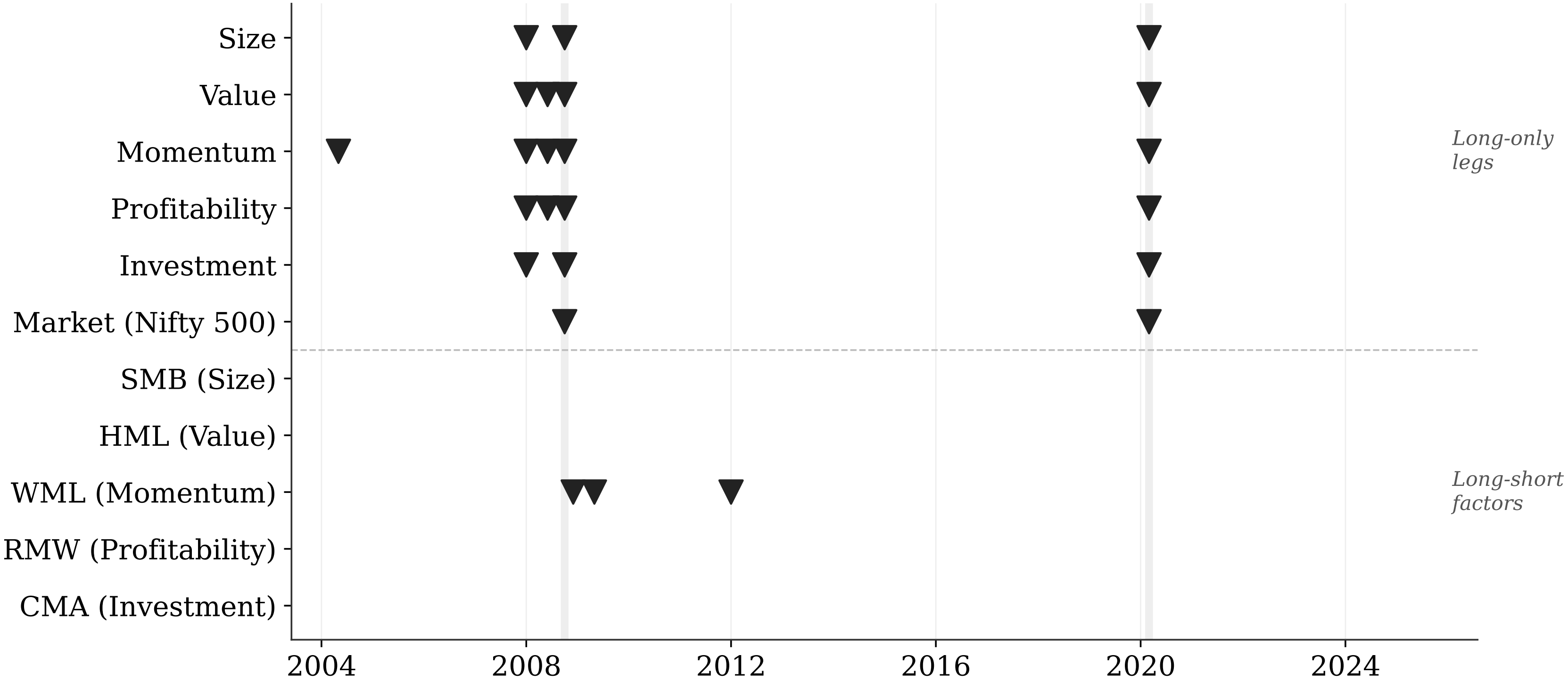

Figure 16: Factor and portfolio crashes, 2003–2026. Each marker is a month in which the indicated series had a return below −20% (a "crash" in the quant vernacular). The long-only legs and the market crash together in the 2008 and 2020 episodes (shaded). Among the long-short factors, only momentum crashes, and in months distinct from the market's; the size, value, profitability, and investment factors never crash.

Table 1
Cross-Sectional Distribution of Stock Prices

Year	p10	p25	median	p75	p90
2005	4.08	8.50	24.58	83.18	247.82
2010	4.90	12.50	36.95	117.90	323.70
2015	2.78	7.99	26.31	112.04	410.25
2020	1.70	6.30	22.75	88.85	349.38
2025	8.06	27.01	96.77	324.40	962.82

Notes: The table reports the cross-sectional percentiles of firm-level median daily closing prices within the holding universe, for selected portfolio years. Year denotes the portfolio year (October of year t to September of year $t+1$). All figures are in ₹.

Table 2
Firm Counts by Year: Full Base and Holding Universe

Year	All Firms	Holding Firms
2000	3,539	858
2001	3,115	670
2002	2,926	705
2003	2,869	771
2004	3,010	1,097
2005	2,978	1,664
2006	3,107	1,760
2007	3,227	1,907
2008	3,241	2,079
2009	3,439	1,797
2010	3,540	2,169
2011	3,727	2,184
2012	3,782	1,995
2013	3,874	1,582
2014	4,047	1,692
2015	4,040	1,953
2016	4,139	1,971
2017	4,261	2,037
2018	4,327	2,118
2019	4,287	1,988
2020	4,295	1,962
2021	4,410	2,179
2022	4,574	2,622
2023	4,909	2,405
2024	5,231	3,126
2025	5,291	3,358

Notes: All Firms is the full CMIE Prowess base with a valid identifier in each year. Holding Firms is the tradable holding universe, i.e. firms remaining after applying the penny-stock, microcap, illiquidity, and negative-book-equity filters. Year denotes the portfolio year (October of year t to September of year $t+1$).

Table 3
Number of Negative Book Equity Firms by Year

Year	Count	Year	Count
2000	264	2013	276
2001	190	2014	353
2002	248	2015	355
2003	277	2016	394
2004	291	2017	327
2005	281	2018	362
2006	244	2019	358
2007	217	2020	382
2008	194	2021	400
2009	219	2022	402
2010	224	2023	391
2011	231	2024	370
2012	268	2025	361

Notes: Count is the number of firms excluded in each year because of negative reported book equity. Year denotes the portfolio year (October of year t to September of year $t+1$).

Table 4
Cumulative Distribution of Firms by Market Capitalization

Firm percentile	Number of firms	Market-cap cutoff (₹cr)	Share of total market cap (%)
Bottom 1%	51	3.7	0.00
Bottom 5%	252	8.0	0.00
Bottom 10%	504	13.7	0.01
Bottom 20%	1,007	29.9	0.03
Bottom 25%	1,259	42.4	0.05
Bottom 50%	2,517	193.3	0.34
Bottom 75%	3,775	1,494.2	2.03
Bottom 90%	4,530	10,756.0	9.61
Bottom 95%	4,782	30,484.7	19.88
Bottom 99%	4,983	163,368.2	52.97
All firms	5,033	1,845,829.3	100.00

Notes: Firms are sorted in ascending order of market capitalization as of September 2025. Each row reports, for the indicated bottom percentile of firms, the number of firms, the market capitalization of the largest firm in that group (the cutoff), and the cumulative share of total market capitalization those firms represent.

Table 5
Factor Construction

Panel A: Long and Short Legs

Factor	Long leg	Short leg	Label update
SMB	$SV + SN + SG$	$BV + BN + BG$	Annual (September)
HML	$SV + BV$	$SG + BG$	Annual (September)
WML	$SW + BW$	$SL + BL$	Monthly (size and momentum)
RMW	$SR + BR$	$SW + BW$	Annual (September)
CMA	$SC + BC$	$SA + BA$	Annual (September)

Panel B: Breakpoints and Labels

Factor	Metric	Breakpoints	Labels
Profitability	Operating Profitability	30/70 pctile	W (Weak), N (Neutral), R (Robust)
Investment	Asset Growth	30/70 pctile	C (Conservative), N (Neutral), A (Aggressive)
Value	Book-to-Market	30/70 pctile	G (Growth), N (Neutral), V (Value)
Momentum	12-1 Month Return	30/70 pctile	L (Loser), N (Neutral), W (Winner)
Size	Market Cap	90th pctile	S (Small), B (Big)

Notes: Panel A gives the long and short legs of each factor and the frequency at which labels are updated. In the leg expressions, the first letter denotes size (S = Small, B = Big) and the second the characteristic label defined in Panel B. Panel B lists the sorting variable, breakpoints, and labels used to assign each stock.

Table 6
Firm Counts by Year Across Methodologies

Year	All Firms	Ours	AJV	JKP
2000	3,539	858	2,027	639
2001	3,115	670	1,565	677
2002	2,926	705	1,677	754
2003	2,869	771	1,845	811
2004	3,010	1,097	2,010	922
2005	2,978	1,664	2,335	1,002
2006	3,107	1,760	2,227	1,272
2007	3,227	1,907	2,369	1,681
2008	3,241	2,079	2,598	1,882
2009	3,439	1,797	2,560	2,151
2010	3,540	2,169	2,705	2,485
2011	3,727	2,184	2,834	3,193
2012	3,782	1,995	2,905	3,417
2013	3,874	1,582	2,758	3,679
2014	4,047	1,692	2,879	3,821
2015	4,040	1,953	2,753	3,771
2016	4,139	1,971	2,716	3,820
2017	4,261	2,037	2,722	3,977
2018	4,327	2,118	2,896	4,005
2019	4,287	1,988	2,860	4,016
2020	4,295	1,962	2,817	4,100
2021	4,410	2,179	3,033	4,219
2022	4,574	2,622	3,232	4,418
2023	4,909	2,405	3,396	4,769
2024	5,231	3,126	3,696	4,699
2025	5,291	3,358	3,938	

Notes: All Firms is the full CMIE Prowess base. Ours, AJV (Agarwalla, Jacob and Varma, 2014), and JKP (Jensen, Kelly and Pedersen, 2023) are the holding-universe firm counts under each methodology. JKP coverage ends in 2024. Year denotes the portfolio year (October of year t to September of year $t+1$).

Table 7
Distribution of Annual Trading Days

Percentile	Our universe	JKP-only firms
p10	234	39
p25	245	88
p50	248	178
p75	249	243
p90	250	248
p95	251	250
p99	256	252
Max	256	256

Notes: Cross-sectional percentiles of the number of days a firm trades per year, for our holding universe and for firms that appear only in the JKP universe. The maximum number of trading days in a year is 256.

Table 8

Long-Only Factor Performance: October 2003 – May 2026

				Annual				
Factor	Description	Cumulative	CAGR	Mean	Excess	Volatility	Sharpe	Max Drawdown
SMB	Size	58.64x	19.68%	22.62%	16.35%	30.08%	0.54	-71.60%
HML	Value	65.36x	20.25%	24.16%	17.88%	33.59%	0.53	-67.01%
WML	Momentum	105.63x	22.82%	23.99%	17.72%	25.25%	0.70	-66.94%
RMW	Profitability	24.09x	15.07%	16.95%	10.68%	23.61%	0.45	-70.88%
CMA	Investment	21.02x	14.38%	17.06%	10.78%	26.44%	0.41	-65.52%
MKT	Market	26.34x	15.52%	17.03%	10.76%	22.31%	0.48	-60.44%
EW	Combination (all five)	49.29x	18.76%	20.96%	14.68%	26.82%	0.55	-68.05%
EW	Combination (ex. momentum)	40.01x	17.68%	20.20%	13.92%	27.52%	0.51	-68.35%

Notes: Long-only value-weighted portfolios over October 2003–May 2026. Cumulative is the terminal value of ₹1 invested at the start of the period, and CAGR the corresponding compound annual growth rate. Mean is the annualized mean monthly return; Excess is Mean less the average risk-free rate (6.27% annualized); Volatility is the annualized standard deviation of monthly returns. Sharpe is the excess return divided by volatility. Max Drawdown is the largest peak-to-trough decline. MKT (Market) is the Nifty 500 TRI total return. The two EW rows are equal-weighted combinations of all five factor legs and of the four legs excluding momentum.

Table 9

Long-Short Factor Performance: October 2003 – May 2026

				Annual			
Factor	Description	Cumulative	CAGR	Mean	Volatility	Sharpe	Max Drawdown
SMB	Size	2.17x	3.47%	4.23%	12.81%	0.33	-35.09%
HML	Value	2.54x	4.19%	5.60%	17.40%	0.32	-68.86%
WML	Momentum	10.24x	10.81%	12.62%	20.64%	0.61	-59.84%
RMW	Profitability	2.11x	3.35%	3.84%	10.38%	0.37	-36.22%
CMA	Investment	2.37x	3.87%	4.18%	8.65%	0.48	-19.61%
EW	Combination (all five)	3.81x	6.08%	6.09%	5.96%	1.02	-16.27%
EW	Combination (ex. momentum)	2.65x	4.39%	4.46%	5.71%	0.78	-17.16%

Notes: Long-short value-weighted factor portfolios over October 2003–May 2026. Cumulative is the terminal value of ₹1 of notional exposure, and CAGR the corresponding compound annual growth rate. Mean is the annualized mean monthly return and Volatility the annualized standard deviation of monthly returns. Because a long-short factor is self-financing, Sharpe is the raw mean return divided by volatility, with no risk-free adjustment. Max Drawdown is the largest peak-to-trough decline. The two EW rows are equal-weighted combinations of all five factors and of the four factors excluding momentum.

Table 10
Market Betas by Five-Year Window

Portfolio	2006–2010	2011–2015	2016–2020	2021–2025
Panel A: Long-only legs				
Size (Small)	1.17	1.21	1.36	1.24
Value	1.17	1.57	1.48	1.32
Momentum (Winner)	1.02	0.83	1.03	1.27
Profitability (Robust)	1.06	0.83	0.96	1.03
Investment (Conservative)	1.11	1.07	1.15	1.13
Panel B: Long-short factors				
SMB (Size)	0.11	-0.00	0.21	0.10
HML (Value)	0.11	0.53	0.48	0.29
WML (Momentum)	-0.31	-0.82	-0.35	0.17
RMW (Profitability)	-0.10	-0.40	-0.27	-0.15
CMA (Investment)	-0.11	0.02	-0.02	0.04

Notes: Each cell is the market beta from a regression of the portfolio's monthly return on the market excess return (the Nifty 500 TRI total return minus the risk-free rate), over the indicated non-overlapping five-year (60-month) window. Long-only legs use returns in excess of the risk-free rate; long-short factors use the raw premium. Windows are anchored at December 2025 and rolled back; the partial window before 2006 is omitted.

Table 11
Factor Performance Comparison Across Methodologies

Factor	Statistic	Ours	JKP	AJV
SMB	CAGR (%)	3.23	3.94	-0.34
	Mean (%)	3.97	4.99	0.89
	Volatility (%)	12.60	14.98	15.67
	Sharpe Ratio	0.32	0.33	0.06
	Max Drawdown (%)	-35.09	-45.73	-57.87
HML	CAGR (%)	2.14	0.17	9.39
	Mean (%)	3.71	1.74	10.59
	Volatility (%)	18.00	17.94	18.07
	Sharpe Ratio	0.21	0.10	0.59
	Max Drawdown (%)	-68.86	-59.52	-49.46
WML	CAGR (%)	10.10	0.49	13.77
	Mean (%)	12.27	3.26	15.09
	Volatility (%)	21.90	21.86	20.40
	Sharpe Ratio	0.56	0.15	0.74
	Max Drawdown (%)	-59.84	-67.12	-52.24
RMW	CAGR (%)	5.68	1.41	
	Mean (%)	6.12	2.58	
	Volatility (%)	10.78	15.19	
	Sharpe Ratio	0.57	0.17	
	Max Drawdown (%)	-34.35	-40.95	
CMA	CAGR (%)	4.11	-0.18	
	Mean (%)	4.43	1.10	
	Volatility (%)	8.96	15.20	
	Sharpe Ratio	0.49	0.07	
	Max Drawdown (%)	-19.61	-53.80	

Notes: Factor statistics over October 2003–March 2023, the common window across the three sources (the AJV series ends in March 2023). Ours, JKP (Jensen, Kelly and Pedersen, 2023), and AJV (Agarwalla, Jacob and Varma, 2014) are each computed identically: CAGR is the compound annual growth rate, Mean the annualized mean monthly return, and Volatility the annualized standard deviation of monthly returns. Sharpe is the raw mean return divided by volatility, with no risk-free subtraction, since the factors are self-financing; a reader who wishes to net out the risk-free rate may subtract the roughly 6% annual Treasury-bill yield. AJV provide only the size, value, and momentum factors.

A Equal-Weighted Factor Portfolios

Our preferred factor construction value-weights the stocks inside each leg, on the view that value weighting reflects what is tradable at scale. The interactive tool also provides an equal-weighted version of every factor, and we report its full-sample performance here. Table A1 mirrors Tables 8 and 9, with the stocks inside each leg equal-weighted rather than value-weighted.

On the long-only side (Panel A), equal weighting raises every leg. The profitability and investment legs—the weakest under value weighting—become the strongest, compounding at 28–29% per year, and the five-leg combination compounds at 25.7%. On the long-short side (Panel B) the effect is milder and uneven: the value and momentum premiums rise (to 6.9% and 14.4% per year) while the size and profitability premiums change little, and the equal-weighted combination earns a Sharpe ratio of 1.17 against 1.02 for its value-weighted counterpart.

These long-only levels should be read with caution. Equal weighting places the same rupee on the smallest eligible firm as on the largest, and because our "big" bucket is the top decile of market capitalization—which still spans mid-caps to mega-caps—equal weighting tilts even that bucket toward smaller, less liquid names. Over our sample, Indian small- and mid-caps compounded far faster than the broad market (which returned 15.5% per year, a 26.3-fold gain), so the equal-weighted long-only legs reach eye-catching multiples; the momentum leg, for instance, grows 254-fold, roughly ten times the market. The pattern is not driven by a handful of outliers—the largest monthly returns are unremarkable—but it accrues disproportionately to stocks that are difficult to trade in size. The long-short premiums, where the small-cap level effect largely cancels between the long and short legs, are correspondingly more modest and more credible.

We therefore treat the value-weighted series as the headline, conservative benchmark and regard these full-universe equal-weighted results as preliminary. As a first step toward the liquidity question, we repeat the exercise on a narrower, more tradable universe—the 500 largest NSE stocks by market capitalization, again equal-weighted within each leg. Table A2 reports the results.

Restricting the universe to the top 500 names sharply moderates the long-only figures. The legs now compound at 18–20% per year (cumulative 41–63-fold) rather than 25–29% (73–300-fold) in the full universe, and momentum is again the strongest leg with profitability just behind—the value-weighted ranking is restored. The five-leg long-only combination earns a Sharpe ratio of 0.57. On the long-short side the premiums shrink further (momentum 9.4%, value 3.4%, and the size, profitability, and investment premiums all below 3% per year), and the equal-weighted combination Sharpe falls to 0.79 from 1.17 in the full universe. Once the smallest and least liquid stocks are removed, in short, the equal-weighted results converge toward the value-weighted ones—consistent with reading the full-universe long-only levels as a small-cap, low-liquidity tilt rather than an implementable premium. Portfolio turnover and transaction costs remain to be quantified before any of the equal-weighted series is treated as a realizable strategy.

Table A1

Equal-Weighted Factor Performance: October 2003 – May 2026

Panel A: Long-only legs

Factor	Description	Cumulative	CAGR	Annual Mean	Annual Excess	Annual Volatility	Sharpe	Max Drawdown
SMB	Size	73.21x	20.85%	24.14%	17.87%	32.02%	0.56	-70.81%
HML	Value	95.73x	22.29%	25.71%	19.44%	33.22%	0.59	-65.63%
WML	Momentum	254.08x	27.67%	28.32%	22.05%	26.74%	0.82	-67.59%
RMW	Profitability	271.63x	28.05%	28.39%	22.12%	26.21%	0.84	-66.44%
CMA	Investment	299.84x	28.61%	29.58%	23.31%	29.13%	0.80	-61.91%
MKT	Market	26.34x	15.52%	17.03%	10.76%	22.31%	0.48	-60.44%
EW	Combination (all five)	179.46x	25.73%	27.23%	20.96%	28.78%	0.73	-65.76%
EW	Combination (ex. momentum)	162.02x	25.16%	26.96%	20.68%	29.54%	0.70	-65.31%

Panel B: Long-short factors

Factor	Description	Cumulative	CAGR	Annual Mean	Annual Volatility	Sharpe	Max Drawdown
SMB	Size	1.77x	2.55%	3.62%	15.00%	0.24	-38.42%
HML	Value	4.58x	6.94%	7.80%	14.75%	0.53	-37.98%
WML	Momentum	21.10x	14.40%	15.29%	18.11%	0.84	-55.96%
RMW	Profitability	2.00x	3.10%	3.53%	9.74%	0.36	-35.76%
CMA	Investment	2.48x	4.09%	4.28%	7.33%	0.58	-17.66%
EW	Combination (all five)	4.58x	6.94%	6.90%	5.90%	1.17	-17.68%
EW	Combination (ex. momentum)	2.85x	4.73%	4.81%	5.97%	0.81	-13.42%

Notes: Factor portfolios formed exactly as in Tables 8 and 9, but with the stocks inside each leg *equal-weighted* rather than value-weighted. Panel A reports the long-only legs and Panel B the long-short premia, over October 2003–May 2026. Column definitions match Tables 8 (long-only, with Excess return over the 6.27% annualized risk-free rate and an excess-return Sharpe) and 9 (long-short, with a raw self-financing Sharpe). MKT is the same Nifty 500 TRI total return as in the value-weighted tables. The EW rows are equal-weighted combinations of the five factor legs and of the four legs excluding momentum. As discussed in the text, the long-only levels are inflated by the equal weighting of small, illiquid stocks and are best read as illustrative rather than implementable.

Table A2

Equal-Weighted Factor Performance, Top-500 Universe: October 2003 – May 2026

Panel A: Long-only legs

				Annual				
Factor	Description	Cumulative	CAGR	Mean	Excess	Volatility	Sharpe	Max Drawdown
SMB	Size	42.84x	18.03%	20.57%	14.30%	27.94%	0.51	-69.62%
HML	Value	41.05x	17.81%	20.76%	14.49%	29.37%	0.49	-60.03%
WML	Momentum	62.76x	20.04%	21.58%	15.31%	24.97%	0.61	-66.83%
RMW	Profitability	56.15x	19.45%	20.66%	14.38%	23.45%	0.61	-66.46%
CMA	Investment	44.61x	18.24%	19.99%	13.72%	25.03%	0.55	-55.71%
MKT	Market	26.34x	15.52%	17.03%	10.76%	22.31%	0.48	-60.44%
EW	Combination (all five)	51.45x	18.99%	20.71%	14.44%	25.25%	0.57	-63.63%
EW	Combination (ex. momentum)	47.89x	18.61%	20.49%	14.22%	25.76%	0.55	-62.98%

Panel B: Long-short factors

				Annual			
Factor	Description	Cumulative	CAGR	Mean	Volatility	Sharpe	Max Drawdown
SMB	Size	1.43x	1.58%	2.21%	11.40%	0.19	-41.62%
HML	Value	2.13x	3.39%	4.29%	13.94%	0.31	-55.78%
WML	Momentum	7.60x	9.36%	11.19%	19.83%	0.56	-64.57%
RMW	Profitability	1.77x	2.56%	3.18%	11.27%	0.28	-41.30%
CMA	Investment	1.46x	1.69%	2.29%	10.98%	0.21	-42.65%
EW	Combination (all five)	2.74x	4.55%	4.63%	5.84%	0.79	-20.50%
EW	Combination (ex. momentum)	1.90x	2.87%	2.99%	5.62%	0.53	-13.91%

Notes: Identical in construction to Table A1, but the universe is restricted to the 500 largest NSE stocks by market capitalization before the factor sorts, and the stocks inside each leg are equal-weighted. Panel A reports the long-only legs and Panel B the long-short premia, over October 2003–May 2026. Column definitions match Tables 8 and 9; the risk-free rate is 6.27% annualized and MKT is the same Nifty 500 TRI total return as in the value-weighted tables. Relative to the full-universe equal-weighted results in Table A1, restricting to the top 500 names markedly lowers the long-only levels and restores the value-weighted ranking of the legs.