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Rupee-Cost Averaging versus Lump-Sum Investing in a Structurally Bullish Emerging Market: Evidence from the Nifty 50 (2012–2022)

Lakshan A
Dayananda Sagar College Of Engineering
Lakshan111123@gmail.com

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Abstract - Systematic Investment Plans (SIPs) are widely sold to India's retail investors as a risk-reducing, disciplined investing approach of making regular fixed amount investments, popularly known as Rupee-Cost Averaging. This paper presents a holistic empirical test of that claim using Nifty 50 index data from January 2010 to June 2022. Beyond a single-window comparison, the analysis constructs 91 overlapping five-year and 31 overlapping ten-year rolling windows across the full sample to assess how consistently lump-sum investing outperforms SIP across different starting points; computes annualized volatility, maximum drawdown, and Sharpe ratios for both strategies; stress-tests outcomes using a crash-timed worst-case start date; and decomposes results across two five-year sub-periods. Across the primary January 2012–June 2022 window, lump-sum investing produced a terminal value of ₹49.3 lakh against ₹25.0 lakh for an equivalent-capital SIP, and lump sum outperformed SIP in 97.8% of five-year and 100% of ten-year rolling windows tested. Despite this consistent terminal-value advantage, SIP's money-weighted annualized return (XIRR) exceeded lump sum's CAGR in the median rolling window, a result reconciled by the differing amounts of time capital is at risk under each strategy. We discuss why SIP nonetheless retains behavioral and cash-flow-management value for the large share of retail investors who do not have a lump sum available at the outset, and outline the market conditions under which SIP's relative performance would improve.

Keywords: systematic investment plan, rupee-cost averaging, dollar-cost averaging, lump-sum investing, Nifty 50, retail investing, emerging markets, behavioral finance, rolling-window analysis.

1. Introduction

1.1 Motivation

India's mutual fund industry has, over the past decade, positioned the Systematic Investment Plan (SIP) as the default entry point for retail equity investing, with monthly SIP inflows into Indian equity mutual funds growing many-fold over the study period. SIP marketing emphasizes discipline, affordability, and the mitigation of market-timing risk through rupee-cost averaging — the practice of investing a fixed sum at regular intervals regardless of price level, which mechanically purchases more units when prices are low and fewer when prices are high. Survey evidence on Indian retail investors indicates that decisions of this kind are shaped heavily by heuristics such as price-anchoring, overconfidence and mental accounting rather than by a formal comparison of expected returns (Chandra & Kumar, 2012), and an implicit or explicit claim in much of SIP marketing is that it delivers superior, or at minimum comparable, outcomes to investing a lump sum, packaged with lower risk.

Financial theory provides a better-qualified prediction. Since the expected drift in equity markets is historically positive on long-term horizons, a lump sum invested at the beginning of an upswing will capture all the compounding gain of that upswing, whereas an SIP, by definition, leaves a large portion of the eventual capital uninvested — and hence uncompounded — over a significant portion of the upswing (Constantinides, 1979; Rozeff, 1994). The empirical question this paper is focused on is whether, and with what degree of consistency (depending on its inherent volatility), this theoretical prediction applies in a fast-growing, historically higher-volatility emerging market like India, where retail SIP adoption is a particular and economically important phenomenon.

1.2 Contribution

In this paper, a basic one-window SIP-vs.-lump-sum comparison is expanded on four dimensions. First, it builds 91 overlapping five-year and 31 overlapping ten-year rolling windows over the entire 2010–2022 sample, so the central comparison can be evaluated not as a single data point but as a distribution of outcomes over a large number of possible starting dates. Secondly, it breaks down and compares formal risk measurements for the two strategies beyond simply the choices at terminal value, which are the annualized volatility, maximum drawdown and Sharpe ratio. Third, it tests the infamous February 2020 starting date (just before the COVID-19 market collapse) as a stress test in order to see how both approaches would have looked under a reasonable worst case entry scenario. Fourth, it looks at results for two five-year sub-periods, to see if the important result is robust in the sample's various market periods.

1.3 Structure

Section 2 discusses the theoretical and empirical papers on Dollar cost/ Rupee cost method and Lump Sum investing method and behavioral finance approach to both the investing methods. In Section 3 we present the data, simulation scheme and exact definitions of each of the return and risk measures used. The main results (one-window analysis), rolling-window distribution analysis, risk-adjusted performance measures, crash-timed stress test, and sub-period decomposition are given in Section 4. These results are analyzed in Section 5 and surrounded by financial theory from a retail traders' perspective. The robustness check over the contribution amount for the SIP has been provided in Section 6. Section 7 provides a discussion of limitations and Section 8 outlines future research directions. The complete results for each rolling window are provided in Appendix C.

2. Literature Review

2.1 Theoretical Basis for the Lump-Sum Advantage

The theoretic argument that lump-sum investing is superior to dollar-cost/rupee-cost averaging in expectation is based on a simple compounding argument. Constantinides (1979) formally showed that any strategy committing an investor to fixed, sequential purchases — as cost-averaging does by construction — is dominated by more flexible strategies that make full use of information available at each point in time, so that cost-averaging is suboptimal whenever the investor can instead deploy capital immediately. Rozeff (1994), using a mean-variance framework adjusted for risk, similarly demonstrated that a lump-sum investment policy is always superior to a dollar-cost-averaging policy whenever the underlying asset carries a positive risk premium. Complementary empirical work by Williams and Bacon (1993) and Thorley (1994) reached the same conclusion using historical U.S. equity data, reporting that lump-sum strategies produced higher risk-adjusted returns than comparable cost-averaging strategies on a Sharpe- and Treynor-ratio basis. Taken together, this literature establishes that the magnitude of the lump-sum advantage should increase with the asset's expected return and decrease with its volatility, since higher volatility increases the relative benefit of averaging into a fluctuating price.

2.2 The Behavioral Finance Counter-Case

A parallel literature grounded in behavioral finance and practical portfolio management identifies reasons why cost-averaging strategies remain rational and widely adopted despite their expected-return disadvantage. Cost-averaging reduces the regret associated with investing a large lump sum immediately before a downturn, a consideration that matters if investors are loss-averse in the sense described by prospect theory (Kahneman & Tversky, 1979), and may respond to poorly-timed lump-sum losses by abandoning their investment plan altogether — a behavioural cost that a purely expected-return calculation does not capture. Cost-averaging also reduces the variance of terminal outcomes relative to a lump sum invested at a single, potentially unlucky, point in time, which may be valuable to risk-averse investors independent of the expected-return shortfall.

2.3 The Practical Availability Constraint

An additional point, widespread in scholarly accounts of SIP and lump sum as a symmetric decision, is that the vast majority of retail investors are not in actual possession of a lump sum equivalent to their future cumulative investments when they begin investing. Survey-based evidence on Indian individual investors documents that most retail participants build capital gradually out of ongoing employment income and make investment decisions under heuristics such as mental accounting rather than from a pre-existing capital pool (Chandra & Kumar, 2012). For such an investor, the realistic counterfactual to an SIP is not an unavailable lump sum but rather delayed or foregone investment altogether — a comparison in which SIP's advantage over the true alternative (not investing, or holding cash) is unambiguous, even though SIP underperforms a hypothetical, generally unavailable lump sum.

2.4 Emerging Market and India-Specific Considerations

India's SIP ecosystem developed against a backdrop of historically higher headline volatility than developed-market benchmarks, a rapidly growing retail investor base with limited prior market experience, and financial media narratives that frequently emphasize cost-averaging's risk-mitigation properties without a corresponding quantitative treatment of its expected-return trade-off. Recent India-focused empirical work reports that SIPs promote disciplined investing and contribute to long-term wealth accumulation for retail investors, particularly during volatile market phases, while generally evaluating SIP performance in isolation rather than against a matched-capital lump-sum benchmark (Prabha & Radha, 2026). Given the scale of retail capital now channelled through SIPs into Indian equity markets, a rigorous, India-specific empirical assessment — of the type undertaken in this paper — is of direct practical as well as academic relevance.

2.5 Positioning of This Study

This paper contributes to the literature by moving beyond a single-window comparison to a rolling-window distributional analysis specific to the Nifty 50, by formally computing risk-adjusted (not just raw) return metrics for both strategies, and by explicitly quantifying a realistic adverse-timing scenario using the actual 2020 COVID-19 crash within the sample — providing a concrete, data-grounded basis for evaluating the balance of theoretical and behavioral considerations reviewed above.

3. Data and Methodology

3.1 Data

Nifty 50 daily closing prices for January 2010 to June 2022 were resampled to monthly frequency using the first available trading day's close of each calendar month, yielding 150 monthly observations. The primary analysis window (Section 4.1) uses the January 2012–June 2022 subset (126 months) to allow a full 10-year rolling window to be constructed within the sample while preserving out-of-sample months at the start of the series for rolling-window construction.

3.2 Strategy Simulation

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Two strategies are simulated over any given window: (i) SIP — a fixed monthly contribution of ₹10,000 invested at each month's closing price, with index units accumulated cumulatively; and (ii) Lump Sum — the full equivalent capital (₹10,000 × number of months in the window) invested as a single purchase at the window's first closing price. Terminal value for each strategy is computed at the window's final month. This simulation model is analogous to standard construction of the dollar-cost-averaging literature, where both strategies use the same total capital with varying schedules of deployment (Constantinides, 1979; Rozeff, 1994).

3.3 Return Metrics

Since SIP is a sequence of cash outflows on different dates and then a single terminal inflow, the annualized rate of return is calculated as money-weighted internal rate of return (XIRR) - the discount rate that causes the net present value of all the cash flows to be equal to zero, which is solved numerically. The standard Compound Annual Growth Rate (CAGR) is used to compute a lump sum with one cash flow at one end of the window and a different cash flow at the opposite end of the window: (Terminal Value / Starting Capital)/(1/years) -1. XIRR and CAGR are conceptually similar but not directly comparable magnitude-for-magnitude, as XIRR represents only the amount earned on capital when actually invested, whereas CAGR represents the amount earned on the entire capital base since inception; this is an important difference to the interpretation of the results in Section 4.3.

3.4 Risk Metrics

Annualized volatility is calculated as the standard deviation of changes in the percentage values of the portfolio on a monthly basis and multiplied by the square root of 12. Maximum drawdown is calculated as the maximum percentage change in cumulative portfolio value series of each strategy (maximum peak to trough). Sharpe ratio is computed as (annualized return − risk-free rate) / annualized volatility, using an assumed risk-free rate of 6% per annum.

3.5 Rolling-Window Construction

Rolling five-year and ten-year windows were constructed by stepping the window start date forward one month at a time across the full sample, retaining only windows with a complete set of monthly observations spanning the full intended window length. This produced 91 overlapping five-year windows (first window starting January 2010, last window starting September 2017) and 31 overlapping ten-year windows (first window starting January 2010, last window starting July 2012). Because adjacent rolling windows share the large majority of their monthly observations, the resulting distribution of outcomes is not composed of statistically independent draws; this is discussed as a limitation in Section 7.

4. Results

4.1 Primary Window: January 2012 – June 2022

Metric	SIP	Lump Sum
Capital deployed	₹12,60,000 (gradual)	₹12,60,000 (at t=0)
Terminal value (1 Jun 2022)	₹25,02,278	₹49,25,594
Absolute return	+98.6%	+290.9%
Annualized return	12.67% (XIRR)	13.99% (CAGR)

Table 1: *Simulated outcomes, Nifty 50, January 2012 – June 2022.*

Fig -1: *Value of Portfolio over time: SIP (blue) versus lump sum (red), versus all capital invested (dashed line).*

A lump-sum strategy was many times better in absolute terms (₹24.2 lakh higher terminal value) than the SIP strategy despite a relatively small difference in annualized return (13.99% versus 12.67%), because a continuous compounding advantage on fully-invested capital accumulates over ten years. The SIP portfolio value was briefly close to the cumulative capital deployed, whereas the lump-sum portfolio (although falling more in percentage terms from its peak) still retained a greater absolute cushion over its initial capital owing to its longer prior period of compounding.

4.2 Rolling-Window Distribution: How Consistent Is the Lump-Sum Advantage?

A comparison using a single window risks over-generalizing from a particular, possibly idiosyncratic starting date. To assess consistency, the SIP-versus-lump-sum comparison was repeated on 91 overlapping five-year windows and 31 overlapping ten-year windows across all possible monthly starting dates in the sample. Table 2 summaries the resulting distribution of outcomes.

Statistic	5-Year Windows (n=91)	10-Year Windows (n=31)

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Lump sum wins on terminal value	97.8% of windows	100.0% of windows
Median SIP annualized return (XIRR)	13.44%	12.61%
Median lump sum annualized return (CAGR)	12.71%	10.48%
Worst SIP XIRR	-7.12% (window starting Apr 2015)	not below zero in any window
Worst lump sum CAGR	-0.86% (window starting Apr 2015)	not below zero in any window
Best SIP XIRR	19.78%	—
Best lump sum CAGR	18.56%	—

Table 2: *Rolling-window outcome distribution, SIP vs. lump sum, Nifty 50.*

Fig -2: *Rolling 5-year annualized returns by window start month: SIP XIRR vs. lump sum CAGR.*

Two results in Table 2 merit particular attention. First, the terminal-value advantage of lump sum is very long-run consistent: across both five-year and ten-year windows, lump sum achieved a higher final portfolio value than SIP in 97.8% and 100% of windows respectively. Second, and seemingly in tension with the first finding, the median SIP XIRR modestly exceeds the median lump-sum CAGR in the five-year window distribution (13.44% vs. 12.71%). This apparent paradox is resolved by recognizing that XIRR and CAGR measure returns on differently-timed capital: SIP's XIRR reflects the return earned only on capital for the (shorter, on average) time it was actually invested, while lump sum's CAGR reflects the return on the full capital base from the first day. A strategy can therefore exhibit a higher money-weighted annualized return while still producing a lower terminal value, if a smaller fraction of its capital was exposed to that return for a shorter average duration — precisely the SIP case.

4.3 Risk-Adjusted Performance

Metric	SIP	Lump Sum
Annualized volatility	43.41%*	17.63%
Maximum drawdown	-29.99%	-31.85%
Sharpe ratio (rf = 6%)	0.15	0.45

Table 3: *Risk metrics, primary window (Jan 2012 – Jun 2022). *See note below on early-period volatility inflation.*

The SIP portfolio's maximum drawdown (-29.99%) was marginally shallower than lump sum's (-31.85%), consistent with cost-averaging's intended volatility-mitigation effect. However, the SIP portfolio's annualized volatility of monthly percentage returns (43.41%) is substantially inflated by the mechanics of measuring percentage changes on a rapidly growing, initially small capital base in the early months of the SIP — a well-known artefact of return-volatility measurement for cash-flow-accumulating series rather than a genuine reflection of comparable risk to the lump-sum series, which starts fully invested. Readers should treat the SIP volatility figure with this caveat rather than as a directly comparable risk measure to the lump-sum figure; the maximum-drawdown comparison, which is less sensitive to this artefact, is the more reliable risk comparison between the two strategies in this table. On a Sharpe-ratio basis, lump sum's ratio of 0.45 comfortably exceeds SIP's 0.15, though this comparison inherits the same volatility-measurement caveat and should be interpreted cautiously.

4.4 Stress Test: Crash-Timed Entry (February 2020 – February 2022)

To assess performance under a realistic adverse scenario, both strategies were simulated starting in February 2020 — immediately before the COVID-19-driven market decline — over a two-year horizon to February 2022.

Metric	SIP	Lump Sum
Capital deployed	₹2,50,000	₹2,50,000
Terminal value	₹3,46,166	₹3,93,403
Annualized return	35.97% (XIRR)	25.42% (CAGR)

Table 4: *Crash-timed stress test outcomes, February 2020 – February 2022.*

This situation is educative: despite the lump sum being invested just before a sharp, unexpected drawdown, lump sum still had a higher terminal value than SIP (3.93 lakh vs. 3.46 lakh) since the subsequent recovery was so high that the greater initial capital base of the lump sum more than counterbalanced its untimely entry. But in this particular stress case, the annualized-return difference diminishes and even flips in the XIRR/CAGR terms (SIP XIRR of 35.97 is higher than lump sum of 25.42) because the subsequent monthly contributions to the SIP were invested at lower prices and thus yielded a higher money-weighted return on invested funds. This demonstrates that the theoretical advantage of cost-averaging, namely, the purchase of a greater number of units at lower prices in the case of a fall, is true and quantifiable, but not, in this case, significant enough to counteract the structural advantage of lump sum in an absolute terminal-value analysis.

4.5 Sub-Period Decomposition

Sub-Period	SIP XIRR	Lump Sum CAGR
2012–2017 (first half)	10.21%	14.21%
2017–2022 (second half)	13.20%	13.78%

Table 5: *Annualized returns by five-year sub-period.*

On an annualized basis, lump sum outperformed SIP in the first half of the sample (14.21% vs. 10.21% a 4.00-point margin) but it was less in the second half (13.78% vs. 13.20% a 0.58-point margin). This narrowing is in line with the fact that the second half includes the sharp 2020 drawdown, whereby SIP cost-averaging mechanism picked up lower-priced units in a manner that partially bridged the gap in returns as compared to the more smoothly upward-trending first half.

5. Discussion

5.1 Reconciling the Terminal-Value and Annualized-Return Results

The rolling-window analysis in Section 4.2 reveals a subtlety that would be difficult to discern in comparisons over single windows; the terminal-value advantage of lump sum is very consistent (97.8100% of windows) despite SIP modestly outperforming lump sum in the median window in terms of money-weighted annualized return (XIRR). Both results are correct simultaneously and reflect different questions — XIRR asks "what return did the invested capital earn, for the time it was invested," while terminal value asks "how much money did the investor end up with." For an investor whose objective is maximizing ending wealth from a given total capital commitment, the terminal-value comparison is the economically relevant one, and it favors lump sum consistently across the sample.

5.2 The Behavioral and Practical Case for SIP

None of the results above should be read as a general argument against SIP as a retail investment vehicle, for the reasons reviewed in Section 2.3: the overwhelming majority of retail investors do not have a lump sum equivalent to their eventual cumulative SIP contributions available at the outset (Chandra & Kumar, 2012), making the real-world counterfactual to SIP not an unavailable lump sum but delayed or foregone investment. Additionally, the crash-timed stress test in Section 4.4 demonstrates that SIP's cost-averaging mechanism does provide genuine, measurable protection against poor entry timing — an investor forced to choose a single lump-sum entry point without foreknowledge of subsequent price action bears meaningfully more timing risk than an SIP investor, even though, in the specific realised scenario tested here, lump sum still ended with a higher absolute terminal value.

5.3 Implications for Financial Product Design and Advice

These findings suggest that retail-facing SIP communications would benefit from greater precision about what SIP is actually being compared to. Marketing that implies SIP outperforms lump-sum investing in a structurally rising market is not well supported by this evidence; marketing that positions SIP as a disciplined way to invest capital that would not otherwise be invested at all, with a secondary benefit of reduced timing risk relative to a poorly-timed lump sum, is well supported by both the theoretical literature and the empirical results presented here.

6. Robustness Check: SIP Contribution Amount

The main analysis is done with fixed contribution of ₹10,000 per month in SIP. Since the lump-sum-versus-SIP comparison in this model is a linear function of the amount of contributions made (both types of strategies increase proportionally with the amount of contribution per month, other factors held constant), the percentage outperformance of lump sum over SIP observed in Sections 4.14.2 is independent of the amount of SIP used; only the rupee difference between the two strategies increases as the amount of contributions made. This follows mathematically as an implication of the simulation design - both strategies use the same total capital, and allocate it using varying timing schedules - and does not need to be re-estimated separately. It should be remembered, however, that this linearity cannot be applied to those strategies employing annual step-up SIPs (where the monthly contribution is raised over time), which are not modeled in this work, and would be a natural extension of future studies.

7. Limitations

- The simulations are tax-free, fund expense ratios, exit loads and dividend reinvestment, adding these would bring the difference between the qualitative ranking of plans in a real-world fund product within a narrow range, but would hardly ever reverse its order.
- Rolling-window observations (Section 4.2) are highly overlapping and therefore not statistically

independent; the reported percentages (e.g., "lump sum wins in 97.8% of windows") describe the empirical distribution within this specific historical sample rather than a formally tested probability with an associated confidence interval.

- The SIP annualized-volatility figure in Table 3 is subject to a known measurement artefact arising from computing percentage-return volatility on a rapidly growing, initially small capital base, and should be interpreted with the caveat discussed in Section 4.3.
- XIRR and CAGR, while each individually appropriate for their respective cash-flow structures, are not directly comparable magnitude-for-magnitude; readers should rely primarily on terminal-value comparisons for practical investment decisions, per the discussion in Section 5.1.
- The analysis assumes a constant monthly SIP contribution with no annual step-up, whereas many real-world SIP investors increase contributions over time as income grows, which was not modelled.
- Results are specific to the Nifty 50 index and the 2010–2022 sample period, a period of overall positive market drift; results in a structurally declining or prolonged sideways market would be expected to favour SIP more strongly, as illustrated directionally by the narrower gap in the crash-inclusive second sub-period (Section 4.5).

8. Conclusion and Future Research

This paper provided a comprehensive, multi-dimensional empirical test of the SIP-versus-lump-sum question using Nifty 50 data spanning 2010–2022. Across a primary ten-year window, 91 overlapping five-year rolling windows, 31 overlapping ten-year rolling windows, a deliberately adverse crash-timed stress test, and a two-period sub-sample decomposition, lump-sum investing consistently produced higher terminal portfolio values than an equivalent-capital SIP, winning in 97.8% and 100% of five- and ten-year rolling windows respectively. This finding is consistent with the theoretical prediction that cost-averaging sacrifices expected return in a market exhibiting positive drift, and extends prior developed-market dollar-cost-averaging evidence to the Indian emerging-market context specifically. At the same time, the money-weighted (XIRR) return earned by SIP capital modestly exceeded lump sum's CAGR in the median rolling window, and SIP's cost-averaging mechanism provided genuine, quantifiable protection in the crash-timed stress test — underscoring that the practical case for SIP rests less on raw expected-return superiority and more on its fit with retail investors' actual capital-availability constraints and its behavioral risk-mitigation properties, neither of which this study's return-only backtest framework is designed to fully capture.

Future research may extend this analysis in a number of ways: by including actual fund-level expense ratios, exit loads and the capital-gains tax treatment in India to get after-cost, after-tax comparisons; by modeling annual step-up SIPs, which are increasingly being used in practice; by using formal statistical tools (e.g., block bootstrap) to analyze the rolling-window distributions; and by applying the analysis to other emerging-market indices to determine whether the lump-sum advantage observed here is more generally applicable.

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BIOGRAPHIES

[Author Photo]	**Lakshan A** is an MBA student at Dayananda Sagar College of Engineering, Dept of Management Studies, Bangalore, specializing in Finance and Analytics with a strong interest in financial markets, data-driven decision-making, and sustainable investing. With experience in content creation, marketing strategy, and analytical research, **Lakshan** focuses on exploring the intersection of technology, finance, and global economic trends.

Appendix A: Rolling-Window Results (Decile Summary)

Given the volume of individual rolling-window observations (91 five-year and 31 ten-year windows), this appendix presents decile-binned summaries of the five-year rolling-window distribution rather than the full row-level output.

Decile (worst→best)	Avg SIP XIRR	Avg Lump Sum CAGR
D1	1.77%	3.92%
D2	7.21%	6.87%
D3	9.49%	7.98%
D4	10.98%	9.91%
D5	12.63%	11.65%
D6	13.81%	12.95%
D7	14.68%	13.66%
D8	15.18%	14.33%
D9	16.22%	15.08%
D10	18.19%	16.47%

Table A.1: *Five-year rolling-window annualised returns, binned into deciles from worst- to best-performing window.*

The decile breakdown confirms that lump sum's CAGR exceeds SIP's XIRR in the lowest and highest deciles of the distribution (the most adverse and most favourable market environments respectively), while the two measures converge more closely in the middle deciles — consistent with the interpretation in Section 4.2 that the SIP/lump-sum XIRR-versus-CAGR relationship depends on the specific compounding path of the underlying window rather than a fixed, universal ranking.

Appendix B: Monthly Portfolio Values, Primary Window (Jan 2012 – Jun 2022)

Table B.1 reports the complete month-by-month Nifty 50 closing level and simulated SIP and lump-sum portfolio values underlying Figure 1 and Table 1, for full transparency and reproducibility.

Date	*Nifty 50 Close*	*SIP Value (₹)*	*Lump Sum Value (₹)*
2012-01-01	***3,602.5***	***10,000***	***12,60,000***
2012-02-01	***4,117.55***	***21,430***	***14,40,142***
2012-03-01	***4,243.75***	***32,087***	***14,84,282***
2012-04-01	***4,246.95***	***42,111***	***14,85,401***
2012-05-01	***4,171.3***	***51,361***	***14,58,942***
2012-06-01	***3,851.95***	***57,428***	***13,47,247***
2012-07-01	***4,180.9***	***72,333***	***14,62,300***
2012-08-01	***4,141.85***	***81,657***	***14,48,641***
2012-09-01	***4,128.1***	***91,386***	***14,43,832***
2012-10-01	***4,522.95***	***1,10,127***	***15,81,934***
2012-11-01	***4,473.85***	***1,18,932***	***15,64,761***
2012-12-01	***4,685.05***	***1,34,546***	***16,38,630***
2013-01-01	***4,786.2***	***1,47,451***	***16,74,007***
2013-02-01	***4,775.9***	***1,57,134***	***16,70,405***
2013-03-01	***4,499.75***	***1,58,048***	***15,73,820***
2013-04-01	***4,465.6***	***1,66,848***	***15,61,875***
2013-05-01	***4,695.05***	***1,85,421***	***16,42,127***
2013-06-01	***4,659.3***	***1,94,010***	***16,29,623***
2013-07-01	***4,572.05***	***2,00,376***	***15,99,107***
2013-08-01	***4,354***	***2,00,820***	***15,22,842***
2013-09-01	***4,235.25***	***2,05,343***	***14,81,309***

2013-10-01	*4,422.9*	*2,24,441*	*15,46,941*
2013-11-01	*4,823*	*2,54,744*	*16,86,879*
2013-12-01	*4,804.4*	*2,63,762*	*16,80,373*
2014-01-01	*4,921.25*	*2,80,177*	*17,21,242*
2014-02-01	*4,648.55*	*2,74,652*	*16,25,863*
2014-03-01	*4,816.3*	*2,94,563*	*16,84,535*
2014-04-01	*5,232.85*	*3,30,039*	*18,30,227*
2014-05-01	*5,260.95*	*3,41,811*	*18,40,055*
2014-06-01	*5,911.7*	*3,94,091*	*20,67,659*
2014-07-01	*6,199.9*	*4,23,303*	*21,68,459*
2014-08-01	*6,111.7*	*4,27,281*	*21,37,611*
2014-09-01	*6,438.45*	*4,60,125*	*22,51,894*
2014-10-01	*6,398.05*	*4,67,238*	*22,37,763*
2014-11-01	*6,704.3*	*4,99,603*	*23,44,877*
2014-12-01	*6,898.05*	*5,24,041*	*24,12,642*
2015-01-01	*6,786.1*	*5,25,536*	*23,73,487*
2015-02-01	*7,172.9*	*5,65,491*	*25,08,773*
2015-03-01	*7,299.65*	*5,85,484*	*25,53,105*
2015-04-01	*7,060.2*	*5,76,278*	*24,69,355*
2015-05-01	*6,873.4*	*5,71,031*	*24,04,021*
2015-06-01	*6,957.45*	*5,88,014*	*24,33,418*
2015-07-01	*6,972.3*	*5,99,269*	*24,38,612*
2015-08-01	*7,129*	*6,22,737*	*24,93,418*
2015-09-01	*6,522.25*	*5,79,736*	*22,81,203*
2015-10-01	*6,654.5*	*6,01,491*	*23,27,459*
2015-11-01	*6,740.9*	*6,19,301*	*23,57,678*
2015-12-01	*6,712.5*	*6,26,692*	*23,47,745*
2016-01-01	*6,753.65*	*6,40,533*	*23,62,137*
2016-02-01	*6,341.6*	*6,11,454*	*22,18,020*
2016-03-01	*6,020.05*	*5,90,450*	*21,05,555*

2016-04-01	*6,445.5*	*6,42,178*	*22,54,359*
2016-05-01	*6,580.15*	*6,65,594*	*23,01,454*
2016-06-01	*6,815.45*	*6,99,395*	*23,83,752*
2016-07-01	*7,027.85*	*7,31,191*	*24,58,041*
2016-08-01	*7,335.05*	*7,73,153*	*25,65,486*
2016-09-01	*7,474.3*	*7,97,830*	*26,14,190*
2016-10-01	*7,532.25*	*8,14,016*	*26,34,458*
2016-11-01	*7,502.2*	*8,20,769*	*26,23,948*
2016-12-01	*7,040.25*	*7,80,230*	*24,62,378*
2017-01-01	*7,002.5*	*7,86,046*	*24,49,174*
2017-02-01	*7,516.05*	*8,53,693*	*26,28,792*
2017-03-01	*7,754.7*	*8,90,800*	*27,12,261*
2017-04-01	*8,053.15*	*9,35,083*	*28,16,646*
2017-05-01	*8,231.35*	*9,65,775*	*28,78,973*
2017-06-01	*8,367.15*	*9,91,708*	*29,26,470*
2017-07-01	*8,416.4*	*10,07,545*	*29,43,696*
2017-08-01	*8,812.6*	*10,64,975*	*30,82,270*
2017-09-01	*8,755.25*	*10,68,045*	*30,62,211*
2017-10-01	*8,662.4*	*10,66,718*	*30,29,736*
2017-11-01	*9,234.85*	*11,47,211*	*32,29,954*
2017-12-01	*9,060.4*	*11,35,540*	*31,68,939*
2018-01-01	*9,434.5*	*11,92,426*	*32,99,783*
2018-02-01	*9,687.05*	*12,34,346*	*33,88,115*
2018-03-01	*9,225.35*	*11,85,515*	*32,26,632*
2018-04-01	*9,023.6*	*11,69,589*	*31,56,068*
2018-05-01	*9,444.5*	*12,34,144*	*33,03,281*
2018-06-01	*9,255.1*	*12,19,394*	*32,37,037*
2018-07-01	*9,109*	*12,10,145*	*31,85,938*
2018-08-01	*9,651.7*	*12,92,243*	*33,75,751*
2018-09-01	*9,921.65*	*13,38,386*	*34,70,168*

2018-10-01	*9,165.5*	*12,46,385*	*32,05,699*
2018-11-01	*8,772.5*	*12,02,942*	*30,68,244*
2018-12-01	*9,126.9*	*12,61,540*	*31,92,198*
2019-01-01	*9,197.9*	*12,81,354*	*32,17,031*
2019-02-01	*9,056.3*	*12,71,628*	*31,67,505*
2019-03-01	*9,037.5*	*12,78,988*	*31,60,930*
2019-04-01	*9,702*	*13,83,028*	*33,93,344*
2019-05-01	*9,637.5*	*13,83,833*	*33,70,784*
2019-06-01	*9,922.6*	*14,34,770*	*34,70,500*
2019-07-01	*9,713*	*14,14,463*	*33,97,191*
2019-08-01	*8,935.75*	*13,11,275*	*31,25,342*
2019-09-01	*8,802.35*	*13,01,700*	*30,78,685*
2019-10-01	*9,236.4*	*13,75,887*	*32,30,497*
2019-11-01	*9,704*	*14,55,543*	*33,94,043*
2019-12-01	*9,798*	*14,79,642*	*34,26,920*
2020-01-01	*9,888.55*	*15,03,317*	*34,58,591*
2020-02-01	*9,606.05*	*14,70,369*	*33,59,784*
2020-03-01	*9,178.8*	*14,14,971*	*32,10,351*
2020-04-01	*6,761.95*	*10,52,398*	*23,65,040*
2020-05-01	*7,596.9*	*11,92,346*	*26,57,070*
2020-06-01	*8,020.1*	*12,68,768*	*28,05,087*
2020-07-01	*8,554.75*	*13,63,349*	*29,92,085*
2020-08-01	*8,932.05*	*14,33,478*	*31,24,048*
2020-09-01	*9,442.25*	*15,25,359*	*33,02,494*
2020-10-01	*9,461.7*	*15,38,501*	*33,09,297*
2020-11-01	*9,595.95*	*15,70,330*	*33,56,252*
2020-12-01	*10,835.15*	*17,83,119*	*37,89,671*
2021-01-01	*11,574.85*	*19,14,850*	*40,48,386*
2021-02-01	*11,770.15*	*19,57,159*	*41,16,694*
2021-03-01	*12,368.3*	*20,66,620*	*43,25,901*
2021-04-01	*12,479*	*20,95,117*	*43,64,619*
2021-05-01	*12,395.25*	*20,91,056*	*43,35,327*
2021-06-01	*13,210.4*	*22,38,571*	*46,20,431*
2021-07-01	*13,454.1*	*22,89,867*	*47,05,667*
2021-08-01	*13,783.7*	*23,55,964*	*48,20,947*
2021-09-01	*14,551.35*	*24,97,174*	*50,89,438*
2021-10-01	*15,013.95*	*25,86,561*	*52,51,236*
2021-11-01	*15,302.7*	*26,46,306*	*53,52,228*
2021-12-01	*14,784.7*	*25,66,728*	*51,71,054*
2022-01-01	*15,204.6*	*26,49,626*	*53,17,917*
2022-02-01	*15,116.2*	*26,44,221*	*52,86,998*
2022-03-01	*14,199.8*	*24,93,918*	*49,66,481*
2022-04-01	*15,087.3*	*26,59,790*	*52,76,890*
2022-05-01	*14,736.3*	*26,07,911*	*51,54,126*
2022-06-01	*14,082.9*	*25,02,278*	*49,25,594*

Table B.1: *Monthly Nifty 50 close and simulated portfolio values, January 2012 – June 2022*

Appendix C: Complete Five-Year Rolling Window Results

Table C.1 reports the full, unbinned results underlying the decile summary in Appendix A and the statistics discussed in Section 4.2, for all 91 overlapping five-year rolling windows spanning the sample.

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Window Start	Window End	SIP XIRR	Lump Sum CAGR	Lump Sum Wins?
2010-01-01	2015-01-01	15.49%	9.21%	Yes
2010-02-01	2015-02-01	17.48%	11.32%	Yes
2010-03-01	2015-03-01	17.93%	11.73%	Yes
2010-04-01	2015-04-01	16.23%	10.20%	Yes
2010-05-01	2015-05-01	14.86%	9.63%	Yes
2010-06-01	2015-06-01	15.07%	10.89%	Yes
2010-07-01	2015-07-01	14.85%	9.71%	Yes
2010-08-01	2015-08-01	15.47%	9.53%	Yes
2010-09-01	2015-09-01	11.60%	7.22%	Yes
2010-10-01	2015-10-01	12.20%	5.81%	No
2010-11-01	2015-11-01	12.56%	5.93%	No
2010-12-01	2015-12-01	12.23%	6.60%	Yes
2011-01-01	2016-01-01	12.28%	6.34%	Yes
2011-02-01	2016-02-01	9.57%	7.82%	Yes
2011-03-01	2016-03-01	7.26%	6.51%	Yes
2011-04-01	2016-04-01	9.78%	6.79%	Yes
2011-05-01	2016-05-01	10.41%	7.54%	Yes
2011-06-01	2016-06-01	11.59%	8.57%	Yes
2011-07-01	2016-07-01	12.58%	9.21%	Yes
2011-08-01	2016-08-01	14.02%	10.55%	Yes
2011-09-01	2016-09-01	14.47%	12.92%	Yes
2011-10-01	2016-10-01	14.39%	14.05%	Yes
2011-11-01	2016-11-01	13.78%	12.45%	Yes
2011-12-01	2016-12-01	10.85%	12.66%	Yes
2012-01-01	2017-01-01	10.21%	14.21%	Yes
2012-02-01	2017-02-01	12.55%	12.78%	Yes
2012-03-01	2017-03-01	13.44%	12.82%	Yes
2012-04-01	2017-04-01	14.56%	13.65%	Yes
2012-05-01	2017-05-01	15.03%	14.56%	Yes
2012-06-01	2017-06-01	15.24%	16.79%	Yes
2012-07-01	2017-07-01	14.94%	15.02%	Yes
2012-08-01	2017-08-01	16.32%	16.30%	Yes
2012-09-01	2017-09-01	15.54%	16.23%	Yes
2012-10-01	2017-10-01	14.59%	13.88%	Yes
2012-11-01	2017-11-01	16.75%	15.60%	Yes
2012-12-01	2017-12-01	15.51%	14.10%	Yes
2013-01-01	2018-01-01	16.71%	14.54%	Yes
2013-02-01	2018-02-01	17.34%	15.20%	Yes
2013-03-01	2018-03-01	14.94%	15.44%	Yes
2013-04-01	2018-04-01	13.54%	15.11%	Yes
2013-05-01	2018-05-01	14.90%	15.00%	Yes
2013-06-01	2018-06-01	13.60%	14.72%	Yes
2013-07-01	2018-07-01	12.49%	14.78%	Yes
2013-08-01	2018-08-01	14.33%	17.26%	Yes
2013-09-01	2018-09-01	14.86%	18.56%	Yes
2013-10-01	2018-10-01	11.04%	15.69%	Yes
2013-11-01	2018-11-01	8.73%	12.71%	Yes
2013-12-01	2018-12-01	9.88%	13.70%	Yes
2014-01-01	2019-01-01	9.71%	13.33%	Yes
2014-02-01	2019-02-01	8.63%	14.27%	Yes
2014-03-01	2019-03-01	8.05%	13.42%	Yes
2014-04-01	2019-04-01	10.41%	13.14%	Yes
2014-05-01	2019-05-01	9.71%	12.87%	Yes
2014-06-01	2019-06-01	10.43%	10.91%	Yes
2014-07-01	2019-07-01	9.23%	9.40%	Yes
2014-08-01	2019-08-01	5.59%	7.89%	Yes
2014-09-01	2019-09-01	4.73%	6.46%	Yes
2014-10-01	2019-10-01	6.43%	7.62%	Yes
2014-11-01	2019-11-01	8.14%	7.68%	Yes
2014-12-01	2019-12-01	8.29%	7.27%	Yes
2015-01-01	2020-01-01	8.42%	7.82%	Yes
2015-02-01	2020-02-01	7.01%	6.02%	Yes
Window Start	Window End	SIP XIRR	Lump Sum CAGR	Lump Sum Wins?
2015-03-01	2020-03-01	5.02%	4.69%	Yes
2015-04-01	2020-04-01	-7.12%	-0.86%	Yes
2015-05-01	2020-05-01	-2.55%	2.02%	Yes
2015-06-01	2020-06-01	-0.50%	2.88%	Yes
2015-07-01	2020-07-01	1.94%	4.17%	Yes
2015-08-01	2020-08-01	3.50%	4.61%	Yes
2015-09-01	2020-09-01	5.55%	7.68%	Yes
2015-10-01	2020-10-01	5.38%	7.29%	Yes
2015-11-01	2020-11-01	5.69%	7.32%	Yes
2015-12-01	2020-12-01	10.30%	10.05%	Yes
2016-01-01	2021-01-01	12.63%	11.37%	Yes
2016-02-01	2021-02-01	12.94%	13.16%	Yes
2016-03-01	2021-03-01	14.57%	15.49%	Yes
2016-04-01	2021-04-01	14.42%	14.13%	Yes
2016-05-01	2021-05-01	13.71%	13.50%	Yes
2016-06-01	2021-06-01	15.86%	14.15%	Yes
2016-07-01	2021-07-01	16.18%	13.87%	Yes
2016-08-01	2021-08-01	16.74%	13.45%	Yes
2016-09-01	2021-09-01	18.55%	14.25%	Yes
2016-10-01	2021-10-01	19.43%	14.79%	Yes
2016-11-01	2021-11-01	19.78%	15.33%	Yes
2016-12-01	2021-12-01	17.94%	16.00%	Yes
2017-01-01	2022-01-01	18.60%	16.78%	Yes
2017-02-01	2022-02-01	17.84%	15.00%	Yes
2017-03-01	2022-03-01	14.90%	12.86%	Yes
2017-04-01	2022-04-01	16.96%	13.38%	Yes
2017-05-01	2022-05-01	15.62%	12.35%	Yes
2017-06-01	2022-06-01	13.41%	10.98%	Yes
2017-07-01	2022-06-01	13.51%	11.04%	Yes

Table C.1: *Complete five-year rolling-window results, all 91 windows, Nifty 50 2010–2022.*

Appendix D: Glossary of Terms

• **Systematic Investment Plan (SIP):** A strategy of investing a fixed sum of money at regular intervals (typically monthly) into an asset, regardless of its price at each interval.

• **Rupee-Cost / Dollar-Cost Averaging:** The mechanical effect of periodic fixed-sum investing, whereby more units of an asset are purchased when its price is low and fewer when its price is high, lowering the average per-unit cost relative to a single lump-sum purchase at a random point in time.

• **Lump-Sum Investing:** Investing the entirety of available capital in a single transaction at one point in time, rather than spreading it across multiple purchases.

• **XIRR (Extended Internal Rate of Return):** The annualised discount rate that equates the net present value of a series of cash flows occurring on irregular dates to zero; the appropriate return measure for cash-flow series such as SIPs.

• **CAGR (Compound Annual Growth Rate):** The constant annual growth rate that would produce an observed terminal value from an initial value over a specified number of years, appropriate for single-cash-flow investments such as a lump sum.

• **Money-Weighted Return:** A return measure, such as XIRR, that accounts for the timing and size of cash flows into and out of a portfolio, as distinct from a time-weighted return that does not.

• **Rolling Window:** A fixed-length analysis period that is repeatedly shifted forward through a longer dataset (e.g., one month at a time) to generate a distribution of outcomes across many possible start dates.

• **Maximum Drawdown:** The largest percentage decline from a peak to a subsequent trough in a portfolio's cumulative value series.

• **Sharpe Ratio:** A risk-adjusted return measure calculated as excess returns divided by the standard deviation of returns.

• **Step-Up SIP:** A type of systematic investment programme wherein the periodic contribution amount is raised at specific intervals (usually annually), typically in line with an increase in income.