WWW.IJRPR.COM

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Risk–Return Classification of Mutual Fund Schemes across 46 Asset Management Companies: A Practice-Based Study at a Pune Distribution Firm

Om Gajendra Mane

School of Business, Indira University, Pune, India
Industry partner: Sanchiit Investments Pvt Ltd, Pune, India
Corresponding author: ommane205@gmail.com

ABSTRACT:

Purpose. To document how a mutual fund distribution firm can screen a wide universe of schemes on risk and return together, and to show what a risk–return matrix built on live data reveals about scheme categories, evaluation horizons and suitability for different investor profiles.

Design. Practice-based study from a two-month on-the-job placement (25 May to 25 July 2026) at Sanchiit Investments Pvt Ltd, Pune. Scheme-level data for 784 entries across 46 asset management companies (AMCs) were compiled from AMC scheme documents, the NGEN and Felix Wealth platforms and AMFI/NSE/BSE sources, cleaned in Excel, and classified into four quadrants (low/high risk × low/high return) using standard deviation, CAGR and 1-, 3- and 5-year returns. A 136-entry illustrative subset is profiled in more detail.

Findings. Low Risk–Low Return was the largest quadrant (327 schemes, 41.7%) and High Risk–Low Return the smallest (107, 13.6%). In the illustrative subset the mean 1-year return ranged from −2.0% to 11.2% across quadrants, while the mean 3-year return ranged from 14.1% to 20.3%; of 46 entries with a negative 1-year return and a reported 3-year return, 28 (61%) had a 3-year return of 10% or more. Hybrid schemes were the most evenly spread across quadrants, and debt sub-categories differed in volatility. A directional reading of SEBI expense slabs suggests a cost gap of roughly 0.5 to 1 percentage point a year between large and small schemes in the same quadrant.

Originality. The study sits between academic theory, which seldom uses a large live dataset, and promotional factsheets, which show favourable metrics for one scheme. It applies one transparent classification logic to a wide cross-section of live schemes. Scheme data are secondary, one set of thresholds was fixed for all sub-categories and expense ratios were not compiled, so the matrix is a first-cut screen and not a cost-adjusted ranking or a recommendation.

Keywords: mutual funds; risk–return matrix; CAGR; standard deviation; scheme classification; investor suitability; India
JEL classification: G11; G23
Article type: Practice-based study

1. Introduction

Indian households are moving savings from gold, property and bank deposits towards market-linked instruments. By mid-2026 industry assets under management (AUM) stood at about ₹82.2 lakh crore across roughly 27.9 crore investor folios and more than 6 crore unique investors, about six times the ₹13.8 lakh crore of mid-2016 (AMFI). Monthly systematic investment plan (SIP) contributions have crossed ₹26,000 crore. Choosing among hundreds of schemes is hard for first-time investors, who often chase recent 1-year returns instead of weighing risk and longer-term performance, and mis-selling remains a risk where recommendations follow commissions and not a documented suitability match.

This paper reports a project carried out at Sanchiit Investments Pvt Ltd, an AMFI-registered mutual fund distribution and advisory firm in Pimpri-Chinchwad, Pune, and asks three questions: **RQ1** how are 784 schemes across 46 AMCs distributed over risk–return quadrants, and how do the four SEBI scheme categories behave; **RQ2** what does a comparison of 1-year with 3- and 5-year returns imply for the horizon used to evaluate schemes; and **RQ3** how can the classification be turned into suitability guidance for conservative, moderate and aggressive investors, and what must be added before it is used with clients. The contribution is a reusable, AMC-wise classification built under one consistent logic. A central caveat applies throughout: scheme figures are secondary data, the quadrant thresholds were fixed once for the whole dataset, and expense ratios were not compiled, so the study demonstrates a screening method and does not rank funds.

2. Theoretical Background

Risk and return. The study rests on the risk–return trade-off: higher potential return is generally linked to higher volatility, so schemes must be compared

on both dimensions together and not on return alone (Markowitz, 1952). Standard deviation of returns is the most widely used proxy for volatility. The compounded annual growth rate (CAGR) smooths year-to-year swings and allows schemes with different holding periods to be compared, while trailing 1-, 3- and 5-year returns show consistency over different windows; 1-year figures are the most exposed to short-term market cycles.

Risk-adjusted measures and cost. Risk-adjusted measures are standard in fund evaluation: the Sharpe ratio divides excess return by standard deviation (Sharpe, 1966), Jensen's alpha measures return over a benchmark after adjusting for risk (Jensen, 1968), and beta, from the capital asset pricing model, measures sensitivity to the market (Sharpe, 1964). The Sortino ratio penalises only downside volatility. These measures need benchmark and return histories that scheme documents do not always supply, so this study uses standard deviation, CAGR and trailing returns. Cost also matters: SEBI caps the total expense ratio (TER) on a slab basis tied to AUM, and a lower TER raises the net return an investor keeps.

Gap. Academic accounts explain these concepts but rarely apply them to a large live scheme universe, while AMC factsheets highlight only favourable metrics for a single scheme. Few studies place a wide cross-section of live schemes under one transparent classification that an advisory team can reuse; this paper addresses that gap.

3. Context and Method

Context. The industry is regulated by SEBI and represented by AMFI, which sets standards and the ARN distributor-certification system. About 44 to 46 AMCs are registered. SEBI's 2017 circular groups schemes into Equity, Debt, Hybrid and Other schemes, and the TER slabs were revised in 2020. Annual SIP contributions rose from about ₹43,921 crore in FY2016-17 to about ₹2,89,000 crore in FY2024-25. Sanchiit Investments Pvt Ltd is a privately held, founder-led firm that serves more than 1,200 clients, executes SIP and lump-sum investments through the NGEN and Felix Wealth platforms and earns distribution commission and advisory fees. Its advisory sequence has three stages: a goal and risk-profile discussion, scheme recommendation and execution, and periodic review. The author worked there as an intern from 25 May to 25 July 2026 under the company mentor, Mr. Pranav Shah (Co-Founder), and a faculty mentor. The first half of the placement was AMC-wise scheme categorisation; the second half combined KYC and onboarding support with N8N-based workflow automation using AI tools.

Design and data. The design is descriptive and analytical. Using purposive sampling around the AMCs the firm tracks, scheme-level data were compiled for **784 entries across 46 AMCs**: scheme name, AMC, AUM (₹ crore), CAGR, 1-, 3- and 5-year returns, standard deviation and the NGEN Score. Missing 3- and 5-year figures, mostly for newer launches, were marked "NA" and never estimated. Before classification the data went through five checks: AMC-name normalisation against a master list using VLOOKUP, unit-consistency checks, flagging of growth and IDCW plans of one scheme so they were not double-counted, manual re-checks of implausible return and risk combinations, and a final comparison of row counts and quadrant totals. Only public scheme-level data were used. **Scheme figures are secondary data; one set of Low/High thresholds was applied to all 784 entries; expense ratios were not compiled; and Tables 3 and 4 and Figure 2 use a 136-entry illustrative subset of 34 schemes per quadrant, whose summary statistics were computed from the subset and are not population estimates.**

Measures. Each scheme is placed in one of four quadrants using standard deviation for risk and CAGR and trailing returns for return:

$$\text{CAGR} = (V_{end} / V_{begin})^{1/n} - 1 \quad (1)$$

$$\sigma = \sqrt{[\ \Sigma\ (r_t - \bar{r})^2 / n\ ]} \quad (2)$$

$$\text{Risk}_i = 1[\sigma_i \geq \theta_\sigma], \quad \text{Return}_i = 1[R_i \geq \theta_R] \quad (3)$$

where 1 means High and 0 means Low, and θ_σ and θ_R are the thresholds fixed once for the dataset; the pair (Risk_i, Return_i) gives the quadrant of scheme *i*. As worked examples, a NAV rising from ₹10 to ₹17.28 in three years gives a CAGR of 20% a year, and annual returns of 18%, 22%, −5%, 30% and 15% (mean 16%) give a standard deviation of about 12%. The classification uses IF and nested-IF formulas in Excel, and pivot tables summarise the results by AMC and quadrant.

4. Results

The work runs in four steps: compile and clean the data, classify each scheme, interpret patterns by category and horizon, and relate the result to investor profiles and cost. The first two answer RQ1, the third RQ2 and the last RQ3.

Key results at a glance

784 / 46 Schemes classified across AMCs	**41.7%** Share in the Low Risk–Low Return quadrant	**61%** Negative 1-year entries with a 3-year return of 10% or more	**0.5–1 pp** Indicative yearly cost gap, large vs small schemes

4.1 Coverage and quadrant distribution (RQ1)

All 784 entries were classified (Table 1, Figure 1). The Low Risk–Low Return quadrant holds the largest share, 327 schemes or 41.7%, consistent with AMC shelves made up mostly of diversified equity, hybrid and debt-oriented schemes and not concentrated bets. The High Risk–Low Return quadrant is the smallest at 107 schemes or 13.6%, which suggests that over the periods analysed most higher-volatility schemes also earned a correspondingly higher return, although that pattern is not guaranteed to continue. Taken together, 523 schemes (66.7%) fall in the two low-risk quadrants and 350 (44.6%) in the two high-return quadrants.

Table 1. Scheme distribution by risk–return quadrant (n = 784)

Quadrant	Description	Schemes	Share
Low Risk – High Return	Lower volatility with relatively higher returns	196	25.0%
High Risk – High Return	Higher volatility, higher-return schemes (sectoral, thematic, small-cap)	154	19.6%

Quadrant	Description	Schemes	Share
Low Risk – Low Return	Lower volatility with comparatively modest returns	327	41.7%
High Risk – Low Return	Higher volatility without a commensurate return premium	107	13.6%
Total	**46 AMCs**	**784**	**100.0%**

Source: author's compilation. Low/High thresholds were fixed once for all 784 entries.

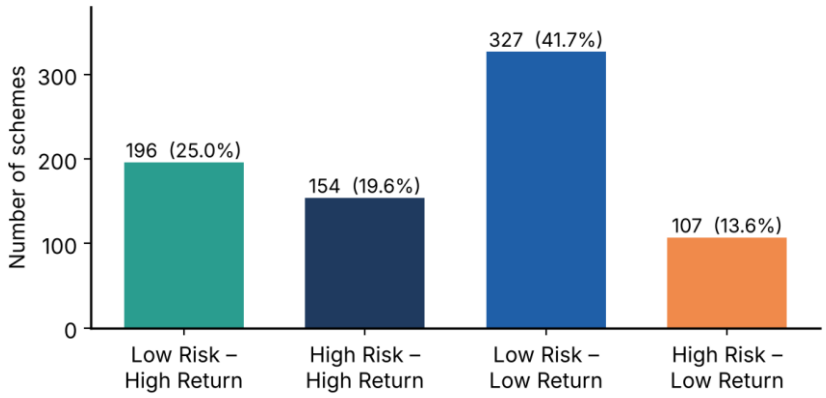


Figure 1. Number and share of schemes by risk–return quadrant (n = 784).

Coverage is weighted towards large, established fund houses (Table 2). The five AMCs with most schemes analysed account for 245 entries (31.3%) and the top ten for 412 (52.6%). This follows from purposive sampling and not from proportional representation of all 46 AMCs, and it broadly mirrors industry AUM concentration: Kotak Mahindra, Nippon India, SBI, Mirae Asset and Axis are all among the ten largest AMCs by AUM.

Table 2. AMCs with the highest number of schemes analysed

Rank	AMC	Schemes analysed	Share of 784
1	Kotak Mahindra Mutual Fund	54	6.9%
2	Nippon India Mutual Fund	51	6.5%
3	SBI Mutual Fund	50	6.4%
4	Mirae Asset Mutual Fund	46	5.9%
5	Axis Mutual Fund	44	5.6%
6	Franklin Templeton Mutual Fund	38	4.8%
7	Groww Mutual Fund	37	4.7%
8	Bandhan Mutual Fund	35	4.5%
9	DSP Mutual Fund	31	4.0%
10	Baroda BNP Paribas Mutual Fund	26	3.3%

Source: author's compilation.

4.2 Category patterns and evaluation horizon (RQ2)

Across the four SEBI categories the 784-entry dataset shows consistent patterns (Table 3). Equity schemes show the widest spread of outcomes, with small-cap, mid-cap and sectoral or thematic schemes occupying most High Risk quadrants. Debt schemes sit almost entirely in the Low Risk quadrants, but credit-risk and long-duration debt show noticeably higher standard deviation than liquid, overnight and ultra-short schemes, a distinction that a single "debt = low risk" label misses. Hybrid schemes are the most evenly spread, reflecting wide differences in equity allocation.

Table 3. Category-wise patterns across the 784 entries

Category	Typical placement	Risk behaviour	Implication
Equity	Small-cap, mid-cap, sectoral and thematic in High Risk quadrants; large-cap and flexicap nearer Low Risk–High Return over 3–5 years	Widest spread of outcomes	Sub-category matters more than the label

Category	Typical placement	Risk behaviour	Implication
Debt	Almost entirely in Low Risk quadrants	Credit-risk and long-duration debt show higher SD than liquid, overnight and ultra-short	"Debt = low risk" hides differences
Hybrid	Most evenly spread across all four quadrants	Equity allocation varies from conservative to dynamic	Label says little without the equity tilt
Other (index funds, ETFs, FoFs)	Follows the underlying index or target fund	Little scope to add or reduce risk	Judge by the underlying index

Source: author's observations from the compiled dataset.

The horizon question is examined in the 136-entry illustrative subset (Table 4, Figure 2). The mean 1-year return falls steadily from 11.2% in Low Risk–High Return to −2.0% in High Risk–Low Return, a spread of about 13 points, whereas the mean 3-year return stays between 14.1% and 20.3%. Of 46 entries with a negative 1-year return and a reported 3-year return, 28 (61%) had a 3-year return of 10% or more. Franklin India Technology Fund illustrates this: a 1-year return of −10.19% sits beside 13.01% over three years and 9.71% over five, which is a clear "avoid" on a 1-year view but a reasonably competitive long-term holding. A 3-year return was reported for 103 of the 136 entries (75.7%) and a 5-year return for 76 (55.9%), reflecting recent launches.

Table 4. Profile of the 136 illustrative entries by quadrant (means, %)

Quadrant	Entries	CAGR	1-year	3-year	5-year	Std. dev.
Low Risk – High Return	34	15.2	11.2	20.3	16.0	17.9
High Risk – High Return	34	15.2	6.1	19.2	15.4	18.9
Low Risk – Low Return	34	11.1	1.1	14.6	11.6	16.2
High Risk – Low Return	34	11.4	−2.0	14.1	12.8	19.7
All entries	**136**	**13.2**	**4.2**	**17.0**	**14.0**	**18.2**

Means exclude NA values. 1-year n = 34, 34, 32, 34; 3-year n = 26, 24, 26, 27; 5-year n = 21, 16, 18, 21. The subset is an equal-sized, representative selection and not a random sample.

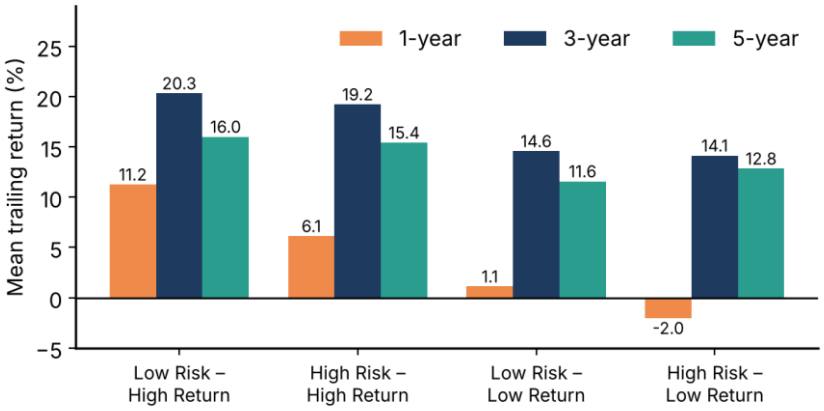


Figure 2. Mean trailing returns by quadrant in the illustrative subset (n = 136; NA values excluded).

Standard deviation matters for suitability. Across the subset it ranges from 10.9% to 38.3% (mean 18.2%). The two low-risk quadrants average 17.9% and 16.2% against 18.9% and 19.7% in the high-risk quadrants, so the Low/High boundary separates risk by only about 2 percentage points on average, which is consistent with one threshold being applied to sub-categories whose natural volatility differs. AUM does not settle placement either: median AUM runs from ₹923 crore to ₹2,169 crore with no consistent ordering by return, and 360 One Focused Fund, with ₹6,537 crore, sits in Low Risk–Low Return beside much smaller schemes.

The longer horizon also fits how investors now save. Annual SIP contributions grew from ₹43,921 crore in FY2016-17 to about ₹2,89,000 crore in FY2024-25, with a single dip in FY2020-21 during the pandemic (Figure 3). Investors who build positions over several years are better served by 3- and 5-year figures than by a 1-year snapshot.

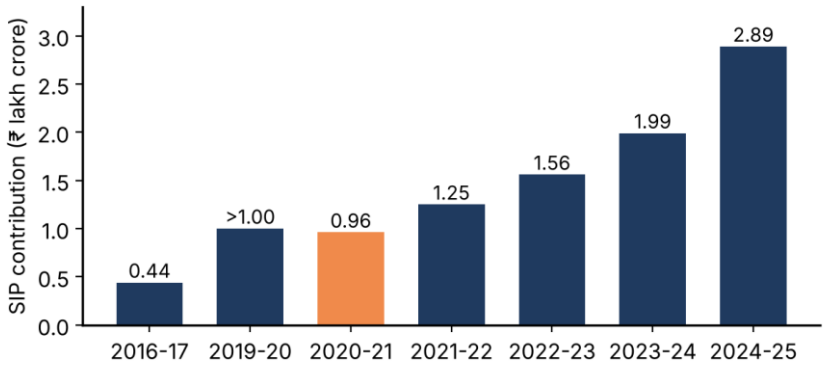


Figure 3. Annual SIP contribution, FY2016-17 to FY2024-25 (₹ lakh crore, approximate; FY2019-20 is reported only as above ₹1 lakh crore; FY2020-21 highlighted).

4.3 Suitability for investor profiles (RQ3)

The classification is meant to feed the recommendation stage of the firm's workflow, giving Relationship Managers a documented reason for suggesting a scheme to a client. Table 5 sets out the guidance that follows from the findings. A client's stated risk tolerance acts as a hard filter that is applied before return figures are discussed, and diversified funds (flexicap, large-cap, multi-cap) suit the core, long-term allocation better than concentrated sectoral or thematic bets.

Table 5. Scheme-selection guidance by investor profile

Profile	Emphasis	Preferred placement	Caution
Conservative	Lower-risk, stable-return schemes	Low Risk quadrants; low-volatility debt sub-categories	Credit-risk and long-duration debt are not low risk
Moderate	Balanced risk–return combination	Low Risk–High Return; diversified equity and hybrid	Check equity tilt of hybrids
Aggressive	High-risk, high-return schemes for long-term wealth creation	High Risk–High Return (sectoral, thematic, small-cap)	Avoid High Risk–Low Return; read 3–5 year data

Source: author's synthesis of the findings. The guidance has not been tested against client outcomes.

4.4 Cost and data quality

The matrix is a pure return and volatility classification and ignores cost. SEBI's 2020 slabs cap the TER from 2.25% on the first ₹500 crore of AUM to 1.05% above ₹50,000 crore for equity schemes, and from 2.00% to 0.80% for debt schemes, so two schemes in one quadrant with very different AUM do not deliver the same net return. Applying the slabs to AUM already reported places large schemes such as Bandhan Large & Midcap Fund (₹16,672 crore) and 360 One Focused Fund (₹6,537 crore) towards the lower end of the permissible range, and small, newly launched schemes such as Bandhan BSE Healthcare Index Fund (₹18 crore) towards the upper end. This suggests a gap of roughly 0.5 to 1 percentage point a year that compounds over a 3- to 5-year holding period. The estimate is directional because no TER figures were compiled.

Data quality affected reliability. A small number of entries with unit inconsistencies or implausible returns were flagged and excluded from the illustrative tables, and newer launches were marked NA and not estimated. A risk–return matrix is only as reliable as the cleaning applied before classification.

5. Discussion

The study shows the risk–return trade-off at work on live data. Comparing schemes on risk and return together (Markowitz, 1952) places two-thirds of schemes in low-risk quadrants and shows that high volatility usually, though not always, came with higher return. The category patterns show that labels are a first filter only: equity, debt and hybrid each contain sub-categories with very different volatility, and index funds simply inherit the risk of their index. The finding that a 1-year view can mislead, since 61% of entries with a negative 1-year return still returned 10% or more over three years, supports using longer windows, in line with the case for risk-adjusted and benchmark-relative measures (Sharpe, 1966; Jensen, 1968). Cost is a fourth dimension that the framework does not yet capture, and the two-point average gap in standard deviation suggests that thresholds set for each sub-category would sharpen the screen. Overall, systematic risk–return analysis gives a stronger and more defensible basis for recommendations than brand reputation or recent headline returns.

Implications for practice. Five practices follow for distribution and advisory firms:

- **Central database:** maintain one standardised, regularly updated scheme database, classified by quadrant and by Conservative, Moderate or Aggressive suitability, with a quarterly refresh and validation at the point of data entry.
- **Profile before scheme:** combine investor risk profiling (objectives, horizon, risk tolerance, existing investments and liquidity needs) with the quadrant before any scheme is suggested.
- **Richer metrics:** add expense ratio, SIP-based XIRR and risk-adjusted measures (alpha, Sharpe and Sortino ratios) alongside CAGR, trailing returns and standard deviation.
- **Dashboard:** develop the Excel framework into a Power BI or advanced Excel dashboard with AMC-wise, category-wise and risk–return views.
- **Automation with oversight:** extend N8N-based automation to periodic data updates and reminders while keeping human verification for

investment analysis, and use the database as decision support and not as an automatic recommendation.

Limitations and future research. Historical returns do not guarantee future returns, and standard deviation does not capture crashes, liquidity or credit events or fund-manager changes. A single set of Low/High thresholds treats small-cap and large-cap schemes alike. Tables 3 to 5 and Figure 2 rest on a representative subset and not the full 784 entries, many newer schemes lack 3- and 5-year data, and some entries had to be excluded as implausible. Expense ratios and tax effects were not analysed, the TER slabs are those of the 2020 framework and later revisions should be checked, and the work covers one firm over about two months at one point in time. Future work should set thresholds for each sub-category, add expense-ratio-adjusted returns and tax efficiency, build a weighted suitability model, extend the matrix to portfolio level and fund-manager due diligence, track schemes across market cycles, and study whether investors choose schemes mainly on recent returns, risk perception, brand or advice.

6. Conclusion

A defensible fund recommendation starts with a consistent screen: compile comparable data, clean it, classify each scheme on risk and return, and read the result with horizon, cost and the client's risk profile in mind. In this study, 784 schemes across 46 AMCs were classified, with 41.7% in Low Risk–Low Return and 13.6% in High Risk–Low Return; 1-year returns varied far more across quadrants than 3-year returns; category labels hid wide differences in sub-category risk; and indicative cost gaps of 0.5 to 1 percentage point a year argue for adding expense ratios. The contribution is a transparent, reusable workflow for a distribution firm, and the natural next step is a cost-adjusted version with sub-category thresholds.

Declarations

Acknowledgements. The author thanks Mr. Pranav Shah, Co-Founder of Sanchiit Investments Pvt Ltd, for guidance and access to live scheme data across 46 AMCs and the NGEN and Felix Wealth platforms, and Dr. Meer Mazhar Ali, OJT Faculty Mentor, School of Business, Indira University, for feedback and support.

Ethics and data. No human participants were studied and no client-identifiable financial information was used. Scheme data are secondary data from AMC scheme documents, the NGEN and Felix Wealth platforms and AMFI/NSE/BSE sources; the quadrant totals and the AMC counts are reported in full in Tables 1 and 2.

REFERENCES :

- Angel One News. (2026). Mutual fund industry sees 21% growth in AUM, reaching ₹81.50 lakh crore in March 2026 [News article].
- Association of Mutual Funds in India. (2026). *Industry AUM, folio and SIP data* [Industry data]. https://www.amfiindia.com/
- Factly. (n.d.). Data: Average monthly SIP contribution increased more than sixfold between 2016-17 and 2024-25 [Data article].
- Groww. (2026). *Top 10 AMC in India 2026: Listed by AUM* [Web article].
- Jensen, M. C. (1968). The performance of mutual funds in the period 1945–1964. *Journal of Finance, 23*(2), 389–416.
- Markowitz, H. (1952). Portfolio selection. *Journal of Finance, 7*(1), 77–91.
- Securities and Exchange Board of India. (2017, October). *Categorization and rationalization of mutual fund schemes* [Circular]. https://www.sebi.gov.in/
- Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *Journal of Finance, 19*(3), 425–442.
- Sharpe, W. F. (1966). Mutual fund performance. *Journal of Business, 39*(1), 119–138.