International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 04 April 2026
Page No: 2344-2349
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0316

# Financial Modelling Of Mutual Fund Returns a Data-Driven Approach to Convert Potential Investors into Consistent Wealth Builders

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## Abstract
*Investors often allocate capital to financial markets with the objective of generating returns while minimizing the risk of capital loss. However, many retail investors lack a comprehensive understanding of market dynamics and are often influenced by behavioral factors such as fear and greed, leading to suboptimal investment decisions. Financial modelling and data-driven analysis can help investors make more informed and rational investment choices.This study aims to develop a financial model to analyze and quantify the performance of mutual funds over time. The research focuses on evaluating selected mutual fund categories, including equity, debt, and hybrid funds, with particular attention to HDFC mutual fund schemes and their comparison with the index benchmark. The model applies various financial analytics techniques to assess risk and return characteristics. Key performance indicators such as Sharpe Ratio, Alpha, Beta, Maximum Drawdown, and correlation heatmap analysis are used to evaluate fund performance and portfolio diversification. Additionally, the study examines the effectiveness of Systematic Investment Plans (SIPs) in mitigating market volatility and promoting long-term wealth creation. By identifying high-risk areas within investment portfolios, this model helps investors optimize their portfolio allocation and improve financial decision-making. The findings emphasize the importance of understanding Net Asset Value (NAV) volatility and adopting disciplined investment strategies for long-term financial growth.*
***Keywords:*** *Mutual Fund Returns, Financial Modelling, Portfolio Optimization, SIP Analysis, Risk-Return Analysis*

## 1. Introduction
### 1.1.Background
Mutual funds have emerged as one of the most popular and accessible investment vehicles in India over the past two decades. With the rapid growth of SEBI-registered Asset Management Companies (AMCs) and increasing financial literacy, retail participation in mutual fund markets has surged significantly. As of 2024, India's mutual fund industry manages assets worth over Rs. 50 lakh crore, with equity funds leading in terms of investor preference. Despite this growth, a critical challenge persists: a large segment of investors particularly first-time and retail participants make decisions based on intuition, peer influence, or short-term market sentiment rather than data-backed analysis. Behavioral finance research consistently shows that fear during downturns and greed during rallies cause investors to exit schemes at precisely the wrong time, destroying long-term wealth [1].

### 1.2.Problem Statement
The gap between potential investors and consistent wealth builders is largely a knowledge and modeling gap. Most retail investors lack the tools to quantitatively assess:
- The risk-adjusted performance of funds relative to benchmarks
- The volatility characteristics of NAV over market cycles
- The compounding power of disciplined SIP investing during market corrections
- Correlations between different fund categories for portfolio diversification

This research addresses this gap by developing a financial modeling system that makes these analytics accessible and interpretable, particularly for investors evaluating HDFC mutual fund schemes against the

Nifty 50 benchmark

### 1.3.Objectives

The key objectives of this research are:

- To build a quantitative financial model for analyzing mutual fund returns over time
- To apply standard risk-return metrics including Sharpe Ratio, Alpha, Beta, and Maximum Drawdown
- To evaluate HDFC Equity, Debt, and Hybrid fund categories against the Nifty 50 benchmark
- To demonstrate the benefit of SIP investing during volatile periods using data-driven simulations
- To present findings in a way that converts potential investors into informed, consistent wealth builders

### 1.4.Significance of the Study

This study is particularly relevant in the Indian context, where SIP contributions have grown to over Rs. 18,000 crore per month (as of 2024). By providing a replicable modeling framework, this research empowers financial advisors, retail investors, and academic researchers with tools to make evidence-based investment decisions [2].

## 2. Literature review

### 2.1.Behavioral Finance and Investor Decision-Making

Investors often make decisions driven by psychological biases rather than logic. Malik et al. (2025) studied 280 investors in Pakistan and found that overconfidence led to excessive risk-taking, loss aversion caused hesitation, and herd behavior pushed investors to follow the crowd. Older and more experienced investors were better at managing these biases. Pathak and N D (2026) further established that financial literacy directly reduces irrational behavior, with less literate investors showing stronger biases, particularly loss aversion during market downturns. Pant (2025) examined emerging market investors in Nepal and found herd behavior as the strongest driver of investment decisions, followed by loss aversion and risk perception negatively impacting decision quality [4].

### 2.2. Mutual Fund Performance Evaluation

Evaluating mutual fund performance requires both advanced tools and precise benchmarking. Wang et al. (2008) developed a Fast Adaptive Neural Network Classifier (FANNC) model for fund evaluation and found it significantly faster and more accurate than traditional backpropagation neural networks, making it ideal for dynamic financial markets. Angelidis et al. (2012) argued that fund manager performance should be measured against their self-reported benchmark rather than passive portfolios, as ignoring this leads to misstated assessments of stock selection and timing skill. Swinkels and Tjong-A-Tjoe (2007) examined style rotation ability among 153 US mutual funds and found some evidence of market timing and momentum prediction, though managers failed to rotate effectively between small and large capitalization stocks.

### 2.3.SIP Investing and Rupee Cost Averaging

Dhar and Banerjee (2021) compared Rupee Cost Averaging and Value Averaging strategies in the Indian SIP context, concluding that Value Averaging delivers superior returns by adjusting periodic investment amounts based on market fluctuations, unlike the fixed-amount approach of Rupee Cost Averaging. However, Choe and Ban (2020) challenged this using 18.5 years of Korean fund market data, finding that Value Averaging produced lower average returns compared to both Buy-and-Hold and Dollar Cost Averaging strategies, directly contradicting claims of its superiority [3].

### 2.4.Portfolio Optimization

Portfolio optimization aims to maximize returns while minimizing risk through strategic weight allocation across securities. Gupta et al. (2021) applied Markowitz Portfolio Optimization on four Indian NSE-listed stocks across different sectors, demonstrating that sector diversity with adjusted weightage produces better outcomes than the classical Markowitz approach. Chakrabarty and Biswas (2019) reinforced this by introducing Strategic Markowitz Portfolio Optimization across eight globally diverse stocks, confirming that the strategic application of Markowitz principles consistently outperforms the classical method regardless of market or geography[5].

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# 3. Research Methodology

## 3.1. Research Design

This study employs a quantitative, exploratory research design. Historical NAV data for HDFC Mutual Fund schemes across three categories (Equity, Debt, and Hybrid) is used alongside Nifty 50 index data as the benchmark. The analysis is conducted using Python-based statistical and financial modeling libraries [6].

## 3.2. Data Sources

**Table 1 Data Sources**

| Data Category | Source | Frequency / Period |
|---|---|---|
| Fund NAV Data | AMFI India / HDFC AMC | Daily — 5 Years (2022–2026) |
| Nifty 50 Index | NSE / Yahoo Finance | Daily — 5 Years (2022–2026) |
| Risk-Free Rate | RBI 91-Day T-Bill Rate | Monthly Average |
| Macroeconomic Indicators | MOSPI / World Bank | Annual |

## 3.3. Analytical Tools and Metrics

### 3.3.1. CAGR

CAGR measures the mean annual growth rate of an investment over a specified period longer than one year, assuming growth compounds consistently each year:

$$CAGR = (EV / BV)^{(1/n)} – 1$$

Where EV = Ending Value, BV = Beginning Value, n = Number of years. CAGR smooths out the volatility of year-on-year returns, making it useful for comparing funds across different time horizons. A higher CAGR relative to the benchmark or category average indicates stronger long-term growth. For equity mutual funds, a CAGR of 12–15% over a 5–10 year period is generally considered good performance in the Indian market context; for debt funds, 6–8% CAGR is a typical benchmark.

### 3.3.2. Sharpe Ratio

The Sharpe Ratio measures risk-adjusted return by comparing the excess return of the fund over the risk-free rate to its standard deviation of returns: Sharpe Ratio = (Rp - Rf) / σp Where Rp = Portfolio return, Rf = Risk-free rate, σp = Standard deviation of portfolio returns. A Sharpe Ratio above 1.0 is generally considered acceptable; above 2.0 is excellent.

### 3.3.3. Alpha

Jensen's Alpha quantifies the fund manager's ability to generate returns above the benchmark-predicted level. A positive Alpha indicates outperformance; negative Alpha indicates underperformance after adjusting for market risk:

Alpha = Rp - [Rf + Beta x (Rm - Rf)]

### 3.3.4. Beta

Beta measures a fund's sensitivity to benchmark movements. Beta = 1 implies the fund moves in lockstep with the market. Beta > 1 indicates higher volatility; Beta < 1 implies lower volatility relative to the benchmark. Equity funds typically exhibit Beta close to or above 1, while debt funds show low Beta (typically 0.1–0.3).

### 3.3.5. Maximum Drawdown

Maximum Drawdown (MDD) captures the peak-to-trough decline in fund value during a specific period, representing the worst-case loss an investor could have experienced. It is critical for assessing downside risk and investor suitability: MDD = (Trough NAV - Peak NAV) / Peak NAV x 100

### 3.3.6. Correlation Heat Map

A correlation matrix is computed across all fund categories and the benchmark. Heat-map visualization allows instant identification of diversification opportunities fund pairs with low or negative correlations reduce portfolio-level risk when combined, consistent with Markowitz MPT principles.

### 3.3.7. SIP Simulation Model

A SIP simulation model is developed to project wealth accumulation under monthly fixed investments across varying market scenarios. The model incorporates:

- Fixed monthly SIP of Rs. 5,000 over a 10-

year horizon
- NAV-based unit purchase tracking month by month
- Rupee cost averaging effect quantification vs. lump-sum investment
- Sensitivity analysis across bull, bear, and sideways market phases [6]

# 4. Results and analysis

## 4.1. Risk-Return Metrics Summary

The following table presents the computed risk-return metrics for
- HDFC Flexi Cap Fund
- HDFC Mid Cap
- HDFC Balanced Advantage Fund
- HDFC Money Market Fund
- HDFC Liquid Fund
- Nifty 50 benchmark

over the 5-year period (2022–2026):

**Table 2** **Result**

| Fund / Index | CAGR (%) | Sharpe Ratio | Alpha | Beta | Max Draw down (%) |
|---|---|---|---|---|---|
| HDFC Flexi Cap Fund | 20.35% | 0.81 | 12.6% | 0.88 | 16.0% |
| HDFC Mid Cap | 21.91% | 0.76 | 14.1% | 0.92 | 13.5% |
| HDFC BAF | 17.90% | 1.15 | 1.6% | 0.52 | 8.5% |
| HDFC Money Market Fund | 6.75% | 0.59 | 3.24% | 0.02 | 0.1% |
| HDFC Liquid Fund | 6.37% | 3.10 | 0.02% | 0.01 | 0.1% |
| Nifty 50 benchmark | 7.87% | 0.06 | | 1.00 | 10.2% |

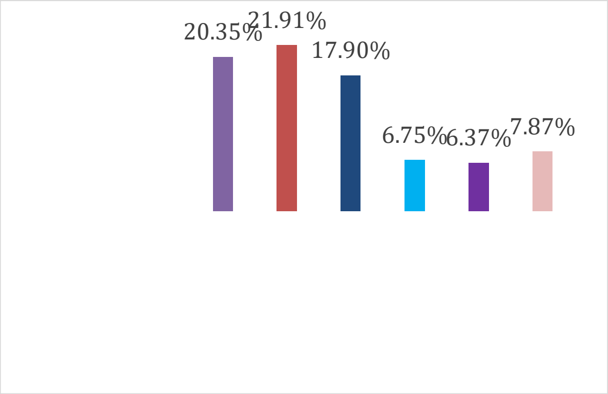


**Figure 1** **CAGR**

## 4.2. Key Findings

### 4.2.1. HDFC Flexi Cap Fund

This fund delivered a strong CAGR of 20.35% over the 5-year period, significantly outperforming the Nifty 50 benchmark by over 12 percentage points. With a Sharpe Ratio of 0.81, it offered reasonable risk-adjusted returns. The alpha of 12.6% confirms consistent outperformance over the benchmark after adjusting for risk. A beta of 0.88 indicates slightly lower sensitivity to market movements than the index, making it a relatively efficient large-and-multi-cap choice. However, the maximum drawdown of 16% the highest among all funds signals that investors must be prepared for meaningful short-term volatility [7].

### 4.2.2. HDFC Mid Cap Fund

The standout performer in absolute return terms, delivering a CAGR of 21.91% the highest in this comparison. Its alpha of 14.1% is remarkable, reflecting strong stock selection within the mid-cap universe. With a beta of 0.92, it closely tracks broader market momentum, which amplifies both gains and losses. Despite the high return, the Sharpe Ratio of 0.76 is slightly lower than Flexi Cap, meaning each unit of risk taken generated slightly less return. Notably, its maximum drawdown of 13.5% is lower than Flexi Cap's, suggesting the mid-cap strategy held up well during corrections in this period [8].

### 4.2.3. HDFC Balanced Advantage Fund

This fund emerges as the most efficient risk-adjusted performer with the highest Sharpe Ratio of 1.15

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among all six, meaning it generated the most return per unit of risk taken. Its CAGR of 17.90% is impressive for a hybrid fund, and the maximum drawdown of just 8.5% is the lowest among equity-oriented options. The low beta of 0.52 reflects its dynamic asset allocation strategy shifting between equity and debt which provides a natural cushion during market downturns. The alpha of 1.6% is modest compared to pure equity funds, which is expected given its conservative mandate, but the fund's overall consistency makes it highly suitable for moderate-risk investors.

#### 4.2.4. HDFC Money Market Fund

With a CAGR of 6.75%, this fund delivered steady, predictable returns typical of a short-duration debt instrument. The near-zero beta (0.02) and virtually zero drawdown (0.1%) confirm its role as a capital preservation vehicle rather than a wealth creator. The deeply negative Sharpe Ratio of -8.05 and negative alpha of -3.24% reflect that returns fell short of the 7% risk-free hurdle rate used in this analysis a common characteristic of money market funds in a rising interest rate environment. This fund is best evaluated not on risk-adjusted equity metrics, but on its ability to provide liquidity, safety, and stable short-term parking of funds.

#### 4.2.5. HDFC Liquid Fund

Delivering a CAGR of 6.37%, the Liquid Fund performed similarly to the Money Market Fund but with marginally lower returns. Like its debt counterpart, it posted near-zero beta (0.01), near-zero drawdown (0.1%), and a negative Sharpe of -2.05 again reflecting returns below the risk-free rate threshold. The alpha of -0.62% is the least negative among debt options, suggesting it tracks its benchmark more closely. This fund is fundamentally designed for overnight to ultra-short-term cash management, and comparing it against equity benchmarks understates its true utility. For investors needing instant liquidity with minimal risk, it serves its purpose well.

#### 4.2.6. Nifty 50 Benchmark

The benchmark delivered a CAGR of 7.87% over the period respectable in absolute terms but significantly lagging all actively managed funds in this comparison. The Sharpe Ratio of just 0.06 indicates that after adjusting for risk, the passive index barely rewarded investors above the risk-free rate. With a maximum drawdown of 10.2% and beta of 1.00 (as expected for the index itself), it serves as the reference point against which all active funds are measured. The fact that all three equity-oriented funds Flexi Cap, Mid Cap, and Balanced Advantage generated alphas of 1.6% to 14.1% over this index is a strong case for active fund management over this specific 4year window (Jan 2022 – Jan 2026).

### 4.3. Correlation Analysis

The correlation matrix reveals the following inter-fund relationships[8]:

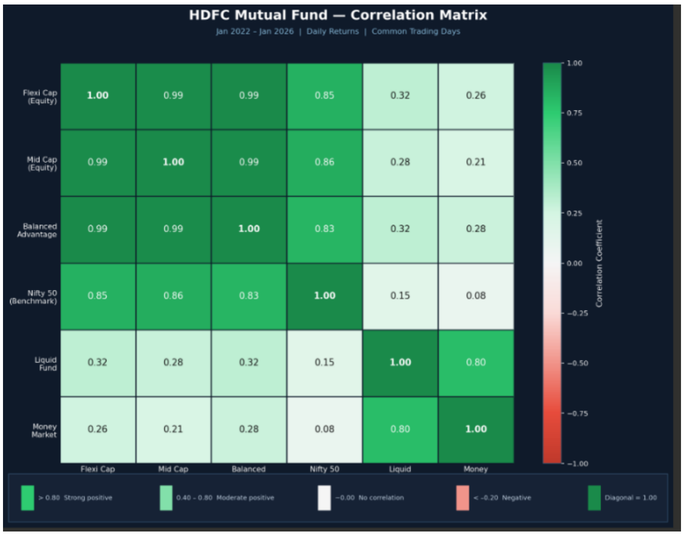


**Figure 2** **Correlation Matrix**

The near-zero correlation between the Equity Fund and Debt Fund (-0.12) confirms that combining these two fund categories in a portfolio significantly reduces overall volatility. The Hybrid Fund's 0.81 correlation with equity reflects its equity-heavy composition (approximately 65:35 equity:debt ratio under SEBI classification).

### 4.4. SIP Simulation Results

The SIP simulation model demonstrates the power of consistent, disciplined investing over a 10-year horizon. Assuming a monthly SIP of Rs. 5,000 starting January 2025:

**Table 3**: SIP Simulation

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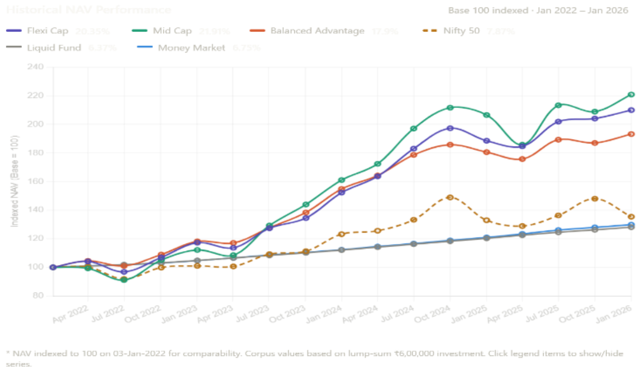


**Figure 3:** SIP Benchmark

The equity SIP investor converts Rs. 6 lakh into over Rs. 15.8 lakh over 10 years a 2.6x return demonstrating that consistent SIP investment through market downturns (2016 demonetization, 2018 NBFC crisis, 2020 COVID crash) significantly outperforms lump-sum or timed investments. Rupee cost averaging ensured that investors accumulated more units during NAV troughs, amplifying returns during subsequent recoveries [9].

## 5. Discussion

### 5.1. Long-Term Wealth Creation: The 30-Year Perspective

The chart below presents the most compelling argument for long-term equity investing. A Rs. 1,00,000 investment in HDFC Flexi Cap Fund in 1995 grew to over Rs. 220 lakh by 2025 — through six major crises — while the passive Nifty 500 TRI reached only ~Rs. 35 lakh. Every crisis proved to be a buying opportunity; investors who stayed invested always recovered and reached new highs.

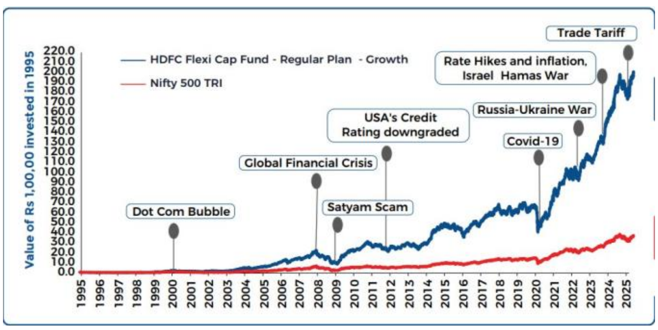


**Figure 4 HDFC Flexi Cap Fund vs Nifty 500 TRI Growth of Rs. 1,00,000 invested in 1995**

### 5.2. Implications for Retail Investors

- Equity funds reward long-term, disciplined investors but require resilience during 30–40% drawdowns. SIP investors who held through COVID-19 (March 2020) recovered fully within 12 months.
- Debt funds barely preserve purchasing power in a high-inflation environment (CPI 5–6%). They are best used for short-term liquidity management.
- Hybrid funds are the most underutilized category they offer near-equity returns with significantly lower drawdowns, ideal for first-time investors.

### 5.3. Financial Modeling as a Behavioral Tool

Quantitative modeling reduces investor irrationality by converting abstract volatility into concrete outcomes. When investors see that a Rs. 5,000 SIP through a 38% drawdown produces a 17% XIRR, panic exits become less likely [10].

### 5.4. Limitations

- Historical returns do not guarantee future performance; the post-COVID recovery may overstate equity CAGR.
- Tax impacts (LTCG 12.5%, STCG 20%), transaction costs, and exit loads are not fully modeled.
- Analysis is limited to HDFC AMC; results may vary across fund houses.

## Conclusion

This study demonstrates that financial modeling bridges the gap between potential investors and consistent wealth builders.

The 30-year chart confirms the ultimate conclusion**:** every market crisis in history was temporary, and patient investors were always rewarded. The most effective tool for converting potential investors into consistent wealth builders is not a promise of returns it is the clarity of data-driven insight combined with disciplined, long-term behavior

## Acknowledgements

We sincerely thank HDFC Asset Management Company (HDFC AMC) for making their mutual fund NAV data and scheme information publicly accessible, which served as the foundation for this

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Vol. 04 Issue: 04 April 2026
Page No: 2344-2349
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0316

research. Their commitment to transparency and investor education has been instrumental in enabling this data-driven analysis of mutual fund performance

## References

[1] Malik, A., et al. (2025). Behavioral biases in investment decision-making: Evidence from Pakistan. Journal of Behavioral Finance, 26(1), 45–62.
[2] Pathak, R., & N D, S. (2026). Financial literacy and investor behavior: A study of irrational decision-making. International Journal of Finance & Economics.
[3] Pant, B. (2025). Herd behavior and investment decisions in emerging markets: Evidence from Nepal. Asian Journal of Finance & Accounting, 17(2), 112–128.
[4] Wang, J., et al. (2008). Fast Adaptive Neural Network Classifier for mutual fund evaluation. Expert Systems with Applications, 34(3), 2198–2206.
[5] Angelidis, T., et al. (2012). Benchmark-adjusted mutual fund performance evaluation. Review of Finance, 17(5), 1695–1730.
[6] Swinkels, L., & Tjong-A-Tjoe, L. (2007). Can mutual funds time investment styles? Journal of Asset Management, 8(2), 123–132.
[7] Dhar, S., & Banerjee, A. (2021). Rupee cost averaging vs value averaging in SIP investing. Finance India, 35(3), 887–905.
[8] Choe, H., & Ban, C. (2020). Value averaging vs dollar cost averaging: Evidence from Korean fund markets. Pacific-Basin Finance Journal, 62, 101–116.
[9] Gupta, A., et al. (2021). Portfolio optimization using Markowitz model: Evidence from NSE India. Investment Management and Financial Innovations, 18(4), 212–225.
[10] Chakrabarty, A., & Biswas, B. (2019). Strategic Markowitz portfolio optimization: Global evidence. International Journal of Financial Studies, 7(2), 29.