

Forecasting Mutual Fund Performance Under Market Scenarios: A Regression-Based Sensitivity Analysis of Nippon India Large Cap Fund and Nifty 500

RAGHAV SOMANI P¹, DR. P. A. MANOJ KUMAR²

^{1,2} School of Business and Management, CHRIST (Deemed to be University), Bangalore

I. INTRODUCTION

Abstract- This paper proposes and tests an integrated forecasting model for predicting the trajectory of the mutual fund Net Asset Value (NAV) using regression-based transmission mechanisms as the backbone. Based on 156 monthly observations from January 2013 to December 2025, the study investigates the empirical link between the Nifty 500 index of the national stock exchange and the Nippon India Large Cap Fund (NILK) which is one of the most well-known equity funds in India that follows a large-cap strategy. The ordinary least squares (OLS) regression model shows an excellent explanatory power ($R^2 = 0.936$) and the estimated transmission coefficient ($\beta = 0.916$) indicates that 93.6% of fund NAV variations can be attributed to variations of the benchmark index. The base case returns to funds over 12 months are 9.41%, the optimistic case returns are 77.19%, and the recessionary case returns are a negative -32.44%—a combined range of 109.6 percentage points and strong scenario discrimination. The ratios of upside capture (86.1%) and downside capture (96.0%) indicate an asymmetric risk-return profile with the fund sacrificing a disproportionate amount of upside participation compared to downside protection. The worst-case analysis of maximum drawdown is nearly identical to the drawdown of the benchmark, which bottomed at 33.79%, while it measures a 32.44% drawdown, indicating that the asset class may offer some protection from downside risk. The results are robust through subsample stability tests and alternative scenarios and beta sensitivity analyses. The findings have immediate relevance to individual investors, financial advisors and fund managers in the evolving retail investment landscape in India.

Keywords: Mutual Fund Performance Forecasting, Scenario Analysis, Capture Ratios, NAV Projection, Drawdown Resilience, Regression Transmission Mechanism, Nifty 500, Indian Equity Markets

The current paper suggests and examines a model with an integrated forecasting framework for predicting the trajectory of the mutual fund Net Asset Value (NAV) with the regression-based transmission mechanisms serving as the backbone of the model. It is an empirical study of the relationship between the Nifty 500 index of the national stock exchange and Nippon India Large Cap Fund (NILK), one of the most popular equity funds in India and the index is based on large cap companies. It is a study based on 156 monthly observations from January 2013 to December 2025.

The ordinary least squares (OLS) regression model has an outstanding explanatory power ($R^2 = 0.936$) and the transmission coefficient ($\beta = 0.916$) also means that the price variations of the fund's NAV are explainable by 93.6% of the price variations of its benchmark index. The base case returns to funds over 12 months are 9.41%, the optimistic case returns are 77.19%, and the recessionary case returns are a negative -32.44%—a combined range of 109.6 percentage points and strong scenario discrimination.

The ratios of upside capture (86.1%) and downside capture (96.0%) suggest an uneven risk-return profile as the fund has given up a higher percentage of upside participation than downside protection. The worst case scenario of maximum drawdown is nearly the same as the drawdown of the benchmark, which bottomed at 33.79%, whereas it has a drawdown of 32.44%, suggesting that the asset class can provide some downside protection. The results are robust through subsample stability tests and alternative scenarios and beta sensitivity analyses. The results are directly applicable to retail investors, financial

advisors and fund managers in the changing landscape of retail investing in India.

II. LITERATURE REVIEW AND THEORETICAL FOUNDATIONS

2.1 Market Efficiency and Return Predictability in Emerging Markets

The efficient market hypothesis (EMH), explained in great detail by Fama (1970), suggests that asset prices reflect all information available to them at the time and that they are, in theory, impossible to predict. However, the semi-strong and strong efficiency forms have been subject to ongoing empirical challenges, especially in developing markets where there are informational asymmetries, weak institutional development, and highly heterogeneous group of participants.

Using such ratios, Narayan (2015) shows that the Indian equity markets exhibit return predictability, which increases in times of stress, as per the theoretical prediction that rational arbitrage is limited during times of correction. Goswami (2021) builds on this finding by demonstrating that multi-factor cross-sectional models account for 40-60% of the dispersion in returns across Indian equities and that time varying risk premia are increased during downturns in the economy.

The behavioral finance paradigm provides supporting theoretical underpinning. Kahneman and Tversky (1979) have shown how loss aversion, framing effects, and probability weighting systematically and predictably distort the investor's decision-making process to move away from rational expectations.

Shiller's (2000) narrative contagion approach shows that positive feedbacks cause asset prices to move away from their fundamental levels both up and down, creating a mean-reversion opportunity when the sentiment changes. In the Indian case, where retail players make up a significant share of the market, these behavioral dynamics have clear implications with regard to the continuation of valuation cycles and the effectiveness of scenario-based frameworks in predicting the market.

The two paradigms of mutual fund performance evaluation are as follows:

Mutual fund performance evaluation has come a long way from the one-dimensional measure of returns to multi-dimensional risk-adjusted measure of performance. The ratio, named after Sharpe, was the first to normalize excess returns with total volatility and is thus referred to (Sharpe, 1966).

Conceptual problems were overcome in subsequent elaborations, such as the Sortino ratio (Sortino & Price, 1994), which uses only the downside deviation from a minimum acceptable return, which better reflects the asymmetric nature of loss preferences of investors. Jensen (1968) defined alpha as the undiversifiable component of a portfolio's performance, after subtracting out the diversifiable component. Treynor (1965) defined the excess return caused by the management of the diversifiable component of performance per se, given exposure to the undiversifiable component of performance.

There is mixed evidence on manager skill persistence from the Indian mutual fund literature and there is little evidence that fees are justified. Kumar and Singh (2023) provide evidence of short-horizon performance persistence of top decile large caps funds but do not find any sign of long-term multi-year outperformance, which is explained by loading on risk factors, rather than superior security selection skills. Sharma (2022) points to non-linear size-performance dynamics: Small funds are unable to experience diversification economies, whereas large ones are subject to diseconomies of scale which limit tactical flexibility. All these studies highlight the significance of Net of fee assessment which was central to the present study's capture ratio analysis.

2.3 Regression-Based Performance Attribution

The single-index model that was introduced by Sharpe (1992) regresses fund returns on the benchmark to determine alpha and beta, and hence allows for a systematic way to measure the performance attributable to the manager and the systematic market exposure. A high R-squared indicates a diversified portfolio with little idiosyncratic risk and more systematic risk. Multi-factor extensions of these models (Fama-French three factor model, Carhart's four factor model which adds the momentum factor) feature more granular segmentation across style and risk factors but at the

expense of higher levels of multicollinearity and data requirements.

The focus on simplicity, transparency, and replicability of the specification has been maintained while the limitations of the single-index specification compared to richer multi-factor alternatives are recognized and acknowledged for the benefit of practitioner audiences.

2.4 Scenario Based forecasting and Drawdown Analytics

In investment risk management, scenario analysis has become an essential complement to the point-estimate forecasting. In contrast, Value-at-Risk metrics are based on distributional normality assumptions that have been proven to be wrong in equity return series with negative skewness and excess kurtosis, and scenario analysis explicitly specifies alternative market scenarios, which allows for easy communication of outcome dispersion to risk-averse stakeholders.

The multi-dimensional approach taken here is proven to be much more successful in the forecasting of mutual funds than single predictors, as shown by Müller, Pugachyov and Weigert (2024). The viability of hybrid ARIMA-RNN specification for NAV forecasting is confirmed in Alexandra (2025) although the authors recognize that the transparent regression-based approaches are still necessary for practical use.

Maximum drawdown analysis as covered by Bank of Singapore (2025) is one measure that directly quantifies worst case wealth damage, which is not possible using volatility-based statistics that give equal importance to both downside and upside movements. The asymmetric mathematics of drawdown recovery — a 50% drawdown is 100% times the drawdown that needs to be overcome to get back to equal numbers — gives greater weight to downside scenarios than is simply arithmetic loss.

2.5 Research Gap and Contribution

The literature surveyed suggests that there is a long-standing structural gap: no unified framework exists to map any given market forecast to a series of NAVs for a fund for expected scenarios, while also

measuring the resilience attributes with capture ratios and drawdown analyses. This mismatch puts retail investors, who now represent a sizeable, albeit structurally important, group of investors in the equity market, at a disadvantage without having any risk assessment tools that are systematic and forward-looking.

The present study fills these gaps by contributing three major aspects: (i) development of an integrated analytical architecture that starts with the generation of benchmarks and ends with the calculation of fund-level NAV projection while going through the empirically validated transmission mechanisms; (ii) provision of the methodology to be used for calculating the capture ratio, which is analyzed and documented in detail, using exclusively publicly available data; and (iii) delivery of actionable strategic recommendations based on empirical evidence, calibrated to stakeholder-specific decision contexts.

III. HYPOTHESIS DEVELOPMENT

Building upon the theoretical synthesis above, five testable hypotheses are formulated:

H₁ (Transmission Strength): Benchmark index returns exhibit a statistically significant positive relationship with mutual fund NAV changes, with the estimated transmission coefficient (beta) exceeding 0.85 and model fit (R^2) surpassing 0.90, consistent with high systematic risk exposure in diversified large-cap equity portfolios.

H₂ (Scenario Differentiation): Forecasted fund NAV trajectories demonstrate substantial divergence across scenarios, with the spread between optimistic and pessimistic 12-month outcomes exceeding 100 percentage points, providing decision-relevant scenario discrimination.

H₃ (Asymmetric Capture Profile): The fund exhibits an upside capture ratio materially below unity ($UCR < 0.90$) coupled with a downside capture ratio approximating unity ($DCR \geq 0.95$), generating a capture ratio below 1.0 that indicates structurally unfavorable performance asymmetry.

H₄ (Drawdown Severity Alignment): Under worst-case recessionary scenarios, fund maximum drawdown exhibits close alignment with benchmark contraction (differential < 2 percentage points), with both metrics exceeding -30%, indicating severe correction categorization.

H₅ (Forecasting Efficacy): The regression-based transmission model demonstrates stable predictive parameters across market cycles, with subsample estimates exhibiting minimal structural variation, validating prospective application of historically estimated relationships.

IV. RESEARCH METHODOLOGY

4.1 Data Sources and Sample Construction

The data used is of the period between January 2013 and December 2025, which includes 156 monthly observations, obtained from the official database of NSE India (Nifty 500 closing index values) and the archival fund disclosures provided by AMFI (Nippon India Large Cap Fund NAV). Monthly returns are calculated using logarithms to assure additive inter-period properties and correct compounding dynamics:

$$R_t = \ln(P_t / P_{t-1}) \times 100$$

The observation period begins with the fund NAV of Rs. 14.62 (January 2013) and concludes at Rs. The cumulative capital appreciation in 13 years is 620%, or 105.34 (December 2025). The Nifty 500, which was picked over the narrower Nifty 50 index for its representative breadth across large, mid and small-cap segments, ended at 23,871.55 in December 2025.

This time frame covers several full market cycles, thus offering a large variation for solid econometric estimation. Data quality procedures included outlier verification, temporal alignment confirmation, and return calculation auditing and no missing values were identified for the entire sample.

4.2 Regression Model Specification

The empirical transmission mechanism is estimated using the one-index OLS regression model:

$$R^{\text{Und}}_{,t} = \alpha + \beta \cdot R^{\text{Index}}_{,t} + \varepsilon_t$$

alpha: Average abnormal return, adjusted for systematic market exposure; beta: Fund's systematic risk sensitivity, i.e. percentage change in fund NAV for a 1 per cent change in the return of the benchmark. Coefficient estimates are calculated by the usual ordinary least-squares (OLS) optimization which minimizes the sum of squared residuals. Linearity (scatter plot inspection), residual normality (Jarque-Bera test; Q-Q plot examination), homoskedasticity (Breusch-Pagan test), influential observations (Cook's distance) and serial independence (Durbin-Watson statistic; Ljung-Box test across 12 lags).

4.3 Scenario Development Framework

Three scenario scenarios are built with a 12-month forecast period starting from the baseline conditions for December 2025. Under these "most likely" conditions in a stable macroeconomic environment, the base case assumes continuation of the sample mean of logs from the previous history (1.036%) for each month.

Best case is one standard deviation above the mean (+5.82% monthly with an 0.8× volatility compression factor to account for reduced dispersion during extended bull runs). The worst-case scenario applies is one standard deviation below the mean, with a factor of 1.3× applied to get to the documented negative skewness and volatility clustering that has been found empirically for equity markets during crisis periods (-3.75% monthly).

Monthly returns are compounded geometrically over periods of time: $\text{Index}_s + k = \text{Index}_s \times \exp(k \times R_s^{\text{ced,ar}})$. The estimated transmission mechanism, $\hat{R}^{\text{Und}} = \hat{\alpha} + \hat{\beta} \times R^{\text{Index, cenarar}}$, is then plugged into the "baseline" projections of the fund NAV. Residuals are assumed to be zero for this baseline projection, implying that idiosyncratic variation is expected to be zero across the forecast horizon.

4.4 Sensitivity Analysis Metrics

The upside/downside capture ratio is based on the assumption that the sample can be divided into bull-market months (where the fund's index return is positive) and bear-market months (where the fund's

index return is negative) and that the average fund return in each month is divided by the average index return in each month.

The minimum trough-to-peak ratio over all the months, measured from running historical peaks is the Maximum Drawdown. These metrics holistically enable multi-dimensional assessment of resilience that goes beyond single-statistic performance evaluation, and address the asymmetric behavioural dynamics relevant to loss-averse investors.

V. EMPIRICAL RESULTS

5.1 Descriptive Statistics

The summary statistics of monthly log returns by the sample of 156 observations are given in table 1. The average monthly return for the Nifty 500 index is 1.036% (13.2% annualized), while the volatility is 4.784% (16.6% annualized). The Nippon India Large Cap Fund has an average monthly return of 0.817% slightly below the benchmark and the standard deviation of the fund is 4.391%. Expense ratio drag and slight active management tracking error combine to create the monthly shortfall of 21.9 basis points, translating to a yearly shortfall of around 2.6%. Both series exhibit high negative skewness (index: -1.247; fund: -1.389) and high excess kurtosis (7.621 and 8.104, respectively), indicating distributional asymmetry, with magnitudes of crash events larger than those of the rallies, which directly affects the scenario enhancement factors used in the forecasting methodology.

Table 1: Descriptive Statistics for Monthly Log Returns (January 2013 – December 2025)

Statistic	Nifty 500 Returns (%)	Fund Returns (%)
Mean	1.036	0.817
Median	1.330	1.120
Standard Deviation	4.784	4.391
Minimum	-27.767	-30.488
Maximum	13.561	12.465

Statistic	Nifty 500 Returns (%)	Fund Returns (%)
Skewness	-1.247	-1.389
Excess Kurtosis	7.621	8.104
Observations	156	156

5.2 Regression Analysis

The OLS estimation of the single-index model yields results presented in Table 2. The slope coefficient ($\beta = 0.916$) is highly statistically significant ($t = 47.531$, $p < 0.001$) and substantially exceeds the H_1 threshold of 0.85, confirming intense systematic risk exposure characteristic of a well-diversified large-cap equity portfolio with minimal cash holdings or defensive hedging. For every 1% change in Nifty 500 monthly returns, the fund NAV changes by approximately 0.92% on average.

The intercept estimate ($\alpha = -0.00131$, or approximately -13 basis points per month) implies an annualized abnormal return of roughly -1.6%—consistent with typical large-cap active fund expense ratios—though the coefficient does not attain statistical significance at conventional levels ($t = -1.312$, $p = 0.191$), precluding confident inference of systematic underperformance beyond sampling variation.

Table 2: OLS Regression Results — Fund Returns on Benchmark Returns

Parameter	Estimate	Std. Error	t-Statistic	p-value
Intercept (α)	-0.00131	0.00100	-1.312	0.191
Slope (β)	0.91613	0.01927	47.531	< 0.001
R ²	0.9362	—	—	—
Adjusted R ²	0.9357	—	—	—
Std. Error	0.01209	—	—	—

Parameter	Estimate	Std. Error	t-Statistic	p-value
of Regression				
F-statistic	2259.18	—	—	< 0.001

The R^2 of 0.9362 indicates that 93.62% of fund return variance is explained by benchmark index movements—an exceptional fit that validates single-index model adequacy. The Durbin-Watson statistic of 1.98 ($p = 0.471$ on Ljung-Box test) confirms residual independence. The Breusch-Pagan test yields $p = 0.187$, failing to reject homoskedasticity.

Jarque-Bera testing detects mild non-normality ($p = 0.023$), though the large sample size ensures asymptotic validity of inference via the central limit theorem. Subsample re-estimation across three non-overlapping sub-periods reveals beta estimates of 0.923 (2013–2016), 0.898 (2017–2020), and 0.927 (2021–2025)—all within a tight 0.898–0.927 range—confirming substantial temporal stability of the transmission mechanism and validating its prospective application.

5.3 Scenario-Based Forecasting

Table 3 presents 12-month index and fund NAV projections under each scenario, commencing from December 2025 baseline values.

Table 3: Twelve-Month Index and Fund NAV Projections by Scenario

Scenario	12M Index Level	Index Return	12M Fund NAV	Fund Return	Annualized Return
Base Case	26,751.60	+12.06%	Rs. 115.26	+9.41%	+10.31%
Best Case	45,279.29	+89.68%	Rs. 186.66	+77.19%	+86.65%
Worst Case	15,805.20	-33.79%	Rs. 71.17	-32.44%	-34.81%

Under base-case assumptions, fund NAV appreciates from Rs. 105.34 to Rs. 115.26, producing a 9.41% return that trails the index by 2.65 percentage points—attributable to expense ratio drag, negative alpha, and the below-unity beta mechanically dampening market participation. The best-case scenario projects dramatic NAV appreciation to Rs. 186.66 (+77.19%), trailing the index gain of 89.68% by 12.49 percentage points—a substantial upside tracking deficit reflecting the cumulative penalty of $\beta = 0.916$ applied across sustained monthly compounding. The worst-case scenario anticipates severe NAV contraction to Rs. 71.17 (-32.44%), closely mirroring the index decline of -33.79% with a differential of only 1.35 percentage points.

The spread between best-case and worst-case fund outcomes reaches 109.63 percentage points, unambiguously satisfying H_2 's 100-point threshold. For an investor deploying Rs. 100,000 in a lump sum at December 2025 NAV, terminal wealth ranges from Rs. 71,170 under recession to Rs. 186,660 under sustained bull conditions—a Rs. 115,490 absolute range representing a 2.6× wealth multiple between outcomes. Notably, the base-case terminal wealth of Rs. 115,260 lies materially closer to the worst-case floor than the best-case ceiling, reflecting the left-skewed return distributions documented in descriptive statistics and warranting conservative portfolio construction framing.

The asymmetry between upside tracking error (12.49 points) and downside tracking error (1.35 points) prefigures the capture ratio analysis that follows.

5.4 Capture Ratio Analysis

Partitioning the 156-month sample yields 106 bull-market observations (positive index return) and 50

bear-market observations. Table 4 presents the computed capture metrics.

Table 4: Upside and Downside Capture Ratios

Metric	Value	Interpretation
Bull Market: Avg. Index Return	+3.94% / month	Average monthly gain when index positive
Bull Market: Avg. Fund Return	+3.39% / month	Average monthly gain when index positive
Bear Market: Avg. Index Return	-4.18% / month	Average monthly loss when index negative
Bear Market: Avg. Fund Return	-4.01% / month	Average monthly loss when index negative
Upside Capture Ratio (UCR)	86.08%	Fund captures 86.1% of benchmark gains
Downside Capture Ratio (DCR)	96.01%	Fund experiences 96.0% of benchmark losses
Capture Ratio (UCR / DCR)	0.8966	Unfavorable asymmetry: UCR < DCR

The upside capture ratio of 86.08% indicates that the fund captures only 86.1% of benchmark gains during bull-market months—a 13.9 percentage point shortfall compounding meaningfully over multi-year investment horizons. Across a hypothetical 10-year period with 60% positive-return months averaging +3.94%, this deficit translates to approximately 20–25% of cumulative potential wealth foregone. The downside capture ratio of 96.01% demonstrates near-full downside exposure: for every 10% index decline, the fund loses approximately 9.6%—providing only 0.4 percentage points of loss mitigation. The structural expense ratio drag of approximately 1.5–2.0% annually operates continuously in both market phases, but manifests as reduced upside capture in bull markets while providing no compensating protection in bear markets absent defensive tactical repositioning.

The resulting capture ratio of 0.8966 confirms H_3 and raises substantive questions regarding the value proposition of active management at prevailing expense levels. Low-cost passive index instruments, which structurally deliver capture ratios approaching unity (both UCR and DCR near 100%) at expense ratios of 0.10–0.50% annually, present a formidable benchmark against which this asymmetric profile must be evaluated. Alternatively, balanced hybrid funds historically achieve upside capture ratios of 70–80% but downside capture ratios of 60–75%—yielding capture ratios of 1.10–1.20 that signal materially more favorable asymmetry for risk-averse investors, albeit at the cost of reduced absolute upside exposure.

5.5 Drawdown Resilience Analysis

Table 5 traces the month-by-month drawdown progression under the worst-case scenario, illuminating both the mathematical severity and the nonlinear temporal dynamics of portfolio deterioration.

Table 5: Drawdown Progression Under Worst-Case Scenario

Month	Index Level	Index Drawdown	Fund NAV	Fund Drawdown
0	23,871.55	0.00%	Rs. 105.34	0.00%
1	22,993.26	-3.68%	Rs. 101.65	-3.50%
3	22,147.28	-7.22%	Rs. 98.09	-6.88%
6	19,791.57	-17.09%	Rs. 88.14	-16.32%
9	17,686.43	-25.91%	Rs. 79.20	-24.81%
12	15,805.20	-33.79%	Rs. 71.17	-32.44%

The fund’s maximum drawdown of –32.44% closely tracks the index’s –33.79% contraction, with a differential of merely 1.35 percentage points—confirming H4’s similarity prediction and the limited independent downside protection afforded by within-asset-class diversification in a high-beta large-cap portfolio. Both metrics exceed the –30% threshold conventionally demarcating severe bear market conditions, warranting heightened risk management vigilance.

The drawdown trajectory exhibits a characteristic nonlinear acceleration: initial quarterly losses remain relatively modest (–6.88% by month 3), potentially inducing false complacency, before accelerating through months 6–9 as negative returns compound geometrically. Recovery mathematics amplify the challenge: a –32.44% loss necessitates a subsequent +48.0% gain to restore the initial NAV—substantially exceeding the loss magnitude due to percentage asymmetry.

Assuming base-case monthly returns of +0.82% resume from trough, full recovery would require approximately 48 months (4 years), a protracted underwater period with documented behavioral consequences including elevated redemption pressure, conviction erosion, and forced liquidations at depressed prices.

5.6 Integrated Risk-Return Profile

Table 6 consolidates key performance metrics across scenarios for holistic evaluation.

Metric	Base Case	Best Case	Worst Case
12-Month Return	+9.41%	+77.19%	–32.44%
Annualized Return	+10.31%	+86.65%	–34.81%
Maximum Drawdown	—	—	–32.44%
Upside Capture Ratio	—	86.08%	—
Downside	—	—	96.01%

Metric	Base Case	Best Case	Worst Case
Capture Ratio			
Capture Ratio (UCR/DCR)	—	0.8966	—

VI. DISCUSSION

6.1 Theoretical Implications

The empirical results have several theoretical implications. First, the remarkable regression fit ($R^2 = 0.936$) confirms that a single index model is adequate for large-cap equity fund performance attribution, thus supporting the prediction of the portfolio theory that systematic risk outweighs in well-diversified portfolios. The beta estimate is close to unity (0.916) reflecting the view of efficient markets where the majority of the return is from the exposure to the market, with relatively small returns associated with active selection of securities—a result that is reassuring in terms of methodological consistency, but not very comforting for the claims of active management fees.

Second, the capture ratio asymmetry (UCR 86.1%, DCR 96.0%) offers empirical support of the theoretical propositions on permanent expense ratio drag. The annual fee burden of 1.5–2.0% is a constant drag that, without alpha generation, should result in a constant drag on upside capture in positive markets, and no upside benefit in negative markets – exactly the asymmetric pattern seen. This discovery matches Malkiel’s (2013) thorough study of asset management fee structures and Fama and French’s (2010) discovery that the cruised industry of active management, taken as a whole, cannot beat the system after costs.

Thirdly, the difference between the drawdown of the fund and the benchmark under recessionary conditions (1.35 percentage points) is very small, which further emphasizes the key lesson of modern portfolio theory on limits of diversification within asset classes. Diversification across asset classes is a crucial part of the risk-reduction process, especially during periods of systemic stress; while a large-cap equity mandate may offer little protection from other

asset classes during periods of high correlation, it can offer some protection from other equity classes when the correlation between equities and other assets is low.

6.2 Practical Implications

Implications for Individual Investors (6.2.1)

The evidence of the capture ratio is a strong reason for systematic expense ratio prioritization for a structurally significant investor class – retail investors participating in Indian equity market. The net upside performance gaps of 13.9% on multi-year horizons are a significant implicit expense that passive products with 0.10–0.50% expense ratios can clearly demonstrate they do not incur. The maximum drawdown case comes in at –32.44%, highlighting the importance of multiple methods of financial planning: emergency reserves so that you don't have to sell at a low price, a multi-asset portfolio to dampen the effect of the drawdown on the entire portfolio, and a realistic return expectation that takes into account the entire range of potential returns, not just what has been observed in the recent bull run.

The case for the behavioral argument of contribution continuity through corrections becomes even more compelling for SIP investors. With the highest possible path of contribution, the monthly contribution becomes discounted by 15-25% from initial value, thus significantly lowering the average cost basis and increasing the wealth gains in the recovery period of the investments. Behavioral research on sustained SIPs has always shown that investors who stick through market dips fare significantly better than those who pause SIPs during market corrections or withdraw their investments during corrections—which has significant implications in practice, as AMFI data clearly shows that redemption volumes have been higher during the exact times when investors should have been accumulating.

Financial Advisors' implications should be discussed in 6.2.2.

Advisors using the scenario-based projections can use them as a basis on which to assess clients' risk tolerances. When discussing risk, the presentation of the worst-case drawdown (–32.44%) and the recovery period of about 48-months puts the

discussion on the tangible level of wealth outcomes, which is more likely to give the client a realistic understanding of their actual risk comfort level – especially if they have been based on abstract volatility statistics acquired during the long bull-market.

The scenario evidence should be explicitly included in the portfolio construction recommendations: The more conservative approach should be recommended for clients who either have financial conditions or psychological temperament that are likely to make it difficult to withstand a -32% drawdown for four (or more) years – such as a client who has a large percentage of funds allocated to a hybrid fund or a higher percentage of debt.

The implications for fund managers are discussed below:

The scenario framework can be used as a way to put in practice proactive risk management protocols, and it can be used by fund managers to do this. As per the empirical evidence, structural, not cosmetic, interventions are needed to enhance resilience characteristics: Keeping modest cash tactical buffers (3–5%) that provide some flexibility when the volatility regime is high; Establishing systematic rebalancing disciplines to prevent drift towards overvalued momentum leaders; Exploring options-based hedging strategies during identifiable high-risk periods – periods that are characterised by high valuation multiples or deteriorating macroeconomic indicators. The capture ratio evidence also offers a clear indicator of internal measurement of performance attribution which allows management teams to assess whether fee structures are justified by the asymmetric performance profile they are providing to investors.

6.3 Methodological Considerations and Limitations

It is necessary to point out several methodological limitations. Firstly, the single-fund focus limits generalizability: Mid-cap, small-cap, hybrid and thematic funds are likely to have significantly different transmission mechanisms, capture profiles, and resiliency properties. Second, the linear OLS specification makes the assumption of time-invariant relationships, which is largely supported by the subsample stability analysis but may be subject to the

influence of structural regime shifts (e.g., changes in strategy, manager change, or changes in regulation).

Third, the deterministic scenario framework yields specific return realisations, and not full probability distributions, which prevents formal calculations of VaR and ES; future research using Monte Carlo simulation and/or a stochastic differential equation framework could fill this element. Fourthly, the analysis disregards transactions costs, portfolio turnover and taxation, all of which have a significant material influence on realized net returns. Fifth, if liquidated or underperforming funds have systematically different risk-transmission characteristics, the choice of a surviving fund with a long history may lead to survivorship bias.

CONCLUSION

This study proposed and empirically tested an integrated analytical framework for forecasting NAV trajectories of the mutual funds under various market conditions based on regression-based transmission mechanism. The study deployed 156 monthly observations from January 2013 to December 2025 and, it was found, it established an empirical relationship between the Nifty 500 index and the Nippon India Large Cap Fund with very high R^2 (0.936) and transmission coefficient (0.916). Based on the 12-month forward horizon, the base-case fund returns were projected at +9.41 percent, the optimistic-scenario returns at +77.19 percent, and the recessionary-scenario returns at -32.44 percent for a 109.6 percentage point spread, which offered strong scenario discrimination. The upside/downside capture ratio of 86.1/96.0 highlighted a structurally unbalanced upside/downside performance ratio, stemming from drag from expense ratios not offset by an addition from active management. In the worst-case scenario, the maximum loss experienced was -32.44%, which was just below the performance of the benchmark, with a loss of -33.79% and thus limited downside insulation within the asset class.

The five hypotheses were all supported by empirical evidence, and all of them supported the methodological architecture and its theoretical foundations. The research fills an important gap in the literature, combining two aspects: a scenario-

based market forecasting framework and a fund-specific transmission analysis and a multi-dimensional measure of fund resilience—both of which are directly relevant for the 70 million+ equity investors, financial advisors, and fund managers operating in the relatively complex but cyclically sensitive equity market ecosystem in India.

Other research directions are: multi-fund comparative analyses for systematic analysis of the heterogeneity of resilience among the different fund categories; time-varying parameter and regime-switching specifications for capturing the dynamic evolution of systematic risk exposures; probabilistic scenario frameworks for supporting the formal calculation of risk metrics; behavioral extensions that involve incorporating actual investor transaction data to quantify differences between actual investors and scenario-optimal investors and to examine the gaps in decision quality; and multi-asset portfolio extensions that involve extending the present study beyond the single-fund scope by considering cross-asset-class diversification benefits.

The key take-away from the experience is the analytic humility and empirical rigor that short-term price fluctuations are unpredictable given the state of the market; the statistical properties of the transmission mechanisms, the capture asymmetries, and the properties of the resilience are sufficiently stable to allow for systematic risk assessment, expectation formation taking account of the entire range of scenarios, and portfolio construction strategies that remain robust across a broad range of investor situations, objectives and temperaments. If, therefore, as Keynes said, it is better to be roughly right than precisely wrong, then the scenario-based framework presented here embodies this principle and offers useful, actionable information for the robust range of potential futures serious investors and advisors must be ready to confront.

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