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ASYMMETRIC ASSET PRICING AND DOWNSIDE RISK SENSITIVITY IN INDIAN MUTUAL FUNDS: EVIDENCE FROM D-CAPM AND LOWER PARTIAL MOMENTS

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ABSTRACT

A growing body of financial literatures support asymmetric and downside-oriented asset pricing frameworks as investors are considerably more sensitive to market downturns. This asymmetry is highly relevant in the mutual fund context where downside protection is the primary concern of risk-averse investors. The applicability of D-CAPM and Lower Partial Moment in the Indian mutual funds, particularly in the post reclassification period, has yet to be systematically examined which constitute a significant research gap. This research empirically evaluates downside risk sensitivity and asymmetric asset pricing of Indian equity mutual funds by employing D-CAPM and LPM_2*. Downside beta estimates are obtained by regressing fund excess returns on market excess returns conditional on negative market movements, while downside risk sensitivity is measured by employing* LPM_2 *with a target return of zero. Using monthly return data for four years, the study examines whether downside risk explains cross-sectional variations in downside risk exposure across funds. Results indicate the existence of substantial variations in downside risk exposure with statistically significant* β^D*. However, cross-sectional regression reveals that* LPM_2 *does not significantly explain variations in* β^D*, suggesting that downside risk and market sensitivity capture distinct risk dimensions. It signifies the importance of asymmetric risk evaluation of mutual funds as these measures yield incremental information.*

Keywords: *Downside CAPM, Lower Partial Moments, Asymmetric Asset Pricing, Downside Beta, Downside Risk, Mutual Funds*

Introduction

Performance evaluation and asset pricing of mutual funds have shifted from symmetric variance-based measures and conventional CAPM to downside-oriented frameworks as investors consider losses during market downturns more significant. Investors exhibit distinct loss aversion attributing considerably higher disutility during downside market fluctuations. Asset pricing literatures have increasingly emphasised unfavourable outcomes rather than focusing on total market variability through Downside beta, D-CAPM and other measures (Estrada, 2002; Mamoghli & Daboussi, 2010; Rutkowska-Ziarko, Markowski, Pyke and Amin, 2022; Markowski, 2024). People attach uneven weight to negative outcomes relative to gains of same magnitude. The tendency called certainty effect in which people underweight outcomes that are merely probable in comparison with outcomes obtained with certainty (Kahneman & Tversky 2013). This behavioural asymmetry resulted the shift of performance evaluation measures to capture asymmetric asset pricing and downside risk sensitivity. Downside risk frameworks, especially, Lower Partial Moment (LPM) and downside CAPM (D-CAPM) capture realistic risk aversion behaviour of mutual fund investors. Bawa and Lindenberg (1977) in their seminal work developed and presented a CAPM model using a mean-lower partial moment framework contributing the early significant literatures and established the foundational mean-LPM CAPM. Among these, second order lower partial moment (LPM_2) jointly captures the frequency and intensity of downside deviations comparative to the target rate of return of the investor. D-CAPM complement this measure by isolating systematic risk during adverse market condition and downturn through the estimate called downside beta (β^D) and downside risk -adjusted abnormal performance (α^D). Despite the growing relevance of downside CAPM and other risk measures, there is a dearth of empirical evidence of their application in mutual funds, especially, across categories of funds. Existing literatures examined the downside risk sensitivity in equity markets with relatively little attention paid on categories of mutual funds, especially in emerging markets, where market declines are often severe and abrupt. In India, the post-reclassification of mutual funds by SEBI has led to the formal introduction of Flexi-cap funds which allow fund managers to dynamically allocate across assets. However, empirical examination of their downside risk and asymmetric risk sensitivity in comparison with Large-cap funds remains unexplored, constitute a significant research gap.

The objective of this study is to conduct a comprehensive empirical evaluation of downside risk sensitivity and asymmetric asset pricing of Indian equity mutual funds, with specific emphasis on flexi-cap and large-cap categories. By integrating second order lower partial moment (LPM_2), D-CAPM, cross- sectional analysis of β^D and independent sample *t* test, the present research provides a comprehensive evaluation of how downside risk sensitivity exists across fund types. The current research advances existing asset pricing literature beyond symmetric variance-based measures particularly in the context of emerging markets offering more investor relevant assessment of downside risk sensitivity. As the study captures downside risk and its intensity, especially in emerging markets, it is highly significant to loss-averse investors and mutual fund performance evaluators. The empirical examination across fund categories, specifically flexi-cap category, provides timely evidence of the effect of increased flexibility on downside sensitivity during market downturns.

Background and Review of Literature

Financial literatures support that the investors are considerably more sensitive to downside deviations than the upside fluctuations, especially during the negative market conditions and this asymmetric behaviour is specifically relevant in the case of portfolio investment. This contributes to the foundational development of downside risk evaluation measures like downside-CAPM and Lower Partial Moment. LPM_2 has been widely adopted as it focusses on adverse market condition and captures the adverse volatility more effectively than the other measures of variance. Within this asymmetric risk behaviour, traditional CAPM model was inadequate to capture the volatility risk during market downturns which constituted the foundation for the development of Downside-Capital Asset Pricing Model. The review of literature is arranged in into two sections. The first section discusses the literatures related to downside CAPM and the second part discusses the literature on lower partial moments.

Downside Risk and Asymmetric Asset Pricing

Bawa & Lindenberg (1977) provided the early theoretical contribution through a model called Mean- Lower Partial Moment. Harlow & Rao (1989) addressed the limitations of prior literatures using a multi-variate approach. Estrada (2001,2002,2004,2006 and 2007) provided an empirical support for downside CAPM with downside beta and supported the superiority of D-CAPM over traditional CAPM; empirically validated downside beta; applied D-CAPM in internet stocks; demonstrated the implementation of D-CAPM for corporate valuation and also confirmed behavioural downside risk premium across markets. Ang, Chen & Xing (2006) in their subsequent literature supported that the downside risk measures contain better explanatory power beyond standard beta specifically during adverse market conditions across markets. Galagedera (2007) using stock return data from emerging markets, supported downside beta and mean-semi variance framework for measuring systematic risk. Pedersen and Hwang (2007), based on UK equity return data, reported that downside beta provides only limited incremental explanatory power over conventional CAPM. In a cross-sectional setting, Galagedera and Brooks (2007) provide evidence that downside co-skewness offers better explanatory power than downside beta in explaining monthly returns in emerging markets. Rutkowska, Markowski & Amin (2022) evaluated conventional and downside CAPM using data from the London stock exchange. Markowski (2024) compared conventional CAPM and downside CAPM with higher order moments and found strong support for the importance of downside risk in the context of standard CAPM.

Lower Partial Moments and Downside Risk Measurement

Building on prior evidence that downside-based risk measures capture systematic risk differently from variance-based metrics, the following strand of literature focuses on lower partial moment, which explicitly account for asymmetric return distributions. Bawa & Lindenberg (1977) developed the foundational CAPM model using a mean-lower partial moment framework, developed early theoretical foundation.

Early empirical valuation of the model was conducted in the following studies. Price, Price & Nantell (1982) focused on variance and LPM based measures to demonstrate systematic risk differ meaningfully across securities with above and below average risk, contributing to early theoretical and empirical development. Lee & Rao (1988) demonstrated Mean-LPM model when security returns are lognormally distributed. Harlow & Rao (1989) provided a theoretical consistency by extending it to arbitrary-order LPM through generalising Mean LPM. Nawrocki (1991) proposed two portfolio-optimization algorithms to capture risk aversion of individual investor. Chow & Denning (1994) recognised the behavioural relevance of downside risk sensitivity.

Eftekhari (1998) found out that lower partial moment hedge ratios are effective in reducing downside risk and increasing returns in case of futures. Unser (2000) examined the individual investor's risk perception using lower partial moment theory, provided experimental and behavioural support.

Mondal & Selvaraju (2019) developed a model called MPLM zero -beta CAPM where risk free assets are lacking. Nesaz et.al (2020) proposed LPM based on multi-period portfolio selection. Mahmoudi et.al (2021) developed genetic algorithm based on a mean-lower partial moment model. Hosseininesaz & Jasemi (2022) incorporated liquidity or inflation risk in LPM and developed asset-liability management model. Hoepner et.al (2024) linked LPM_2 and ESG framework, constitute the contemporary development and portfolio applied extensions in the field of lower partial moments.

Despite these methodological advances, empirical applications of Downside CAPM have been concentrated primarily on equity markets, with relatively limited extension to mutual fund performance evaluation and a continued reliance on traditional CAPM or multi-factor extensions that do not explicitly capture downside market exposure. Consequently, the applicability of downside CAPM and downside risk magnitude as captured by LPM_2 frameworks to Indian mutual funds, particularly in the post reclassification period, has yet to be systematically examined which constitute a significant research gap. By integrating second-order lower partial moment and the downside CAPM, this study quantifies downside risk, estimates downside-adjusted performance and examines category-level differences in downside exposure among equity mutual funds.

Data and Methodology

Research Design and Data

The present study follows a quantitative and ex post facto research design based on secondary time-series data to examine downside risk, downside market sensitivity and category-level differences between Flexi-cap and Large-cap mutual funds in the Indian market.

Actively managed Indian equity mutual funds, comprising flexi-cap and large-cap funds, constitute the sample for the study. Funds were initially drawn based on the four star and above rating given by the Value Research and restricted to open-ended, actively managed, growth and regular plans to avoid heterogeneity arising from dividend options or direct plans. Only schemes explicitly incorporating "Flexi-cap" in their nomenclature were retained in order to maintain categorical precision following the post reclassification period by SEBI. Further, funds were refined by retaining the one which are having expense ratio below two percent and an inception period prior to 2020 for ensuring operational maturity. This process produced eight flexi-cap funds and eleven large-cap funds. From these, three large-cap funds were excluded on the basis of their expense ratios approaching the threshold and lower net asset values, thereby ensuring comparability and sample parity between fund categories. This has resulted in a final sample of eight flexi-cap and eight large-cap funds.

Monthly fund returns were calculated using month-end NAVs of selected funds for four years from April 2021 to March 2025. For computing excess returns, Nifty 500 TRI and Nifty 50 TRI were proxied respectively for flexi-cap and large-cap funds. Equivalent monthly market excess returns were computed for the four years by taking 91-day Treasury Bill yields published by the Reserve Bank of India.

The empirical analysis of the present study follows four stages arranged sequentially to evaluate asymmetric asset pricing, downside risk sensitivity, cross-sectional dependence and differences across categories of funds. The theoretical and mathematical descriptions of these are presented below:

Measurement of Downside Risk: Lower Partial Moment (LPM_2)

Downside risk sensitivity, in the present study, is measured using second-order Lower Partial Moment (LPM_2), that penalises only negative deviations from the target return of zero. Here, greater weights are assigned to larger losses.It is computed using:

$$LPM_2 = \frac{1}{}\sum_{=1}^{T} [max\ (0,0-Rt]^\wedge 2$$

Downside CAPM Estimation

Downside CAPM is used for assessing downside risk and asymmetric asset pricing which are estimated by using only negative return observations.

The downside CAPM is specified as:

$R_{i,t} - R_{f,t} = \alpha_i^D + \beta_i^D (R^{-}_{m,t} - R_{f,t}) + \varepsilon_{i,t}$

Cross-Sectional Regression of Downside Beta on LPM_2

A cross-sectional regression was estimated to evaluate whether the downside market sensitivity is explained by downside risk magnitude using the following equation:

$\beta_i^D = \gamma_0 + \gamma_1 LPM_{2,i} + \varepsilon_i$

Hypotheses

Empirical analysis is based on the following hypotheses:
H_1: $\alpha_i^D \neq 0$
H_2: $\gamma_1 \neq 0$
H_3: μFlexi-cap $\neq \mu$Large-cap

Model Fit and Diagnostic Statistics

The model fit and validity of downside CAPM framework is examined by using goodness-of-fit and other measures like R, R^2, adjusted R^2, F-statistic and standard error of the estimate. All these measures collectively examine the explanatory power of the model during market downturns.

Comparison of Downside Risk Across Fund Categories

Finally, differences in downside risk between fund categories are examined using an independent-samples t-test based on mean LPM_2 values. Given the violation of the homogeneity of variance assumption, Welch's t-test is applied. The test evaluates whether the average downside risk differs significantly between categories, with results reported using the t-statistic, degrees of freedom, mean difference, p-value and 95% confidence interval.

Results and Discussion

This section presents the empirical findings of the study beginning with the assessment of downside risk exposure using LPM_2 followed by the estimation of downside systematic risk through D-CAPM and subsequently examines the relationship between β^D and realized downside deviations. Prior to model estimation, the distributional properties of sampled mutual funds and corresponding market excess returns were evaluated using the Shapiro–Wilk test and results indicate that the normality assumption is fully satisfied with $p > 0.05$.
Table 1 reports the second-order Lower Partial Moment estimates for the selected equity mutual funds based on 48 monthly observations from April 2021 to March 2025.

Table 1: Descriptive Evidence on Downside Risk

Fund	N	LPM_2	Fund	N	LPM_2
FC 1	48	3.4377	LC 1	48	4.6588
FC 2	48	3.8253	LC 2	48	4.3531
FC 3	48	8.8955	LC 3	48	3.9734
FC 4	48	6.12	LC 4	48	5.1198
FC 5	48	5.2493	LC 5	48	5.1073
FC 6	48	7.5777	LC 6	48	4.8129
FC 7	48	6.1684	LC 7	48	4.3756
FC 8	48	8.4503	LC 8	48	4.5303

The empirical results of LPM_2 indicate that the downside risk is substantially heterogeneous across funds. Higher dispersion exists in the case of flexi-cap funds, signifying higher severity of downside risk during market downturns. Contrary to this, large-cap funds exhibit more stable downside volatility which is consistent with the investment mandates of the category. In both the cases, considering the target rate of return as zero, there was relatively significant downside risk experienced by the investors.

Table 2: ***Downside CAPM Estimates***

Fund		t-Statistic	p-value		t-Statistic α^D	p-value (α^D)		Durbin-Watson

	βD	(β^D)	(β^D)	α D			R^2	
FC 1	0.777	8.365	< 0.001	3.072	7.736	< 0.001	0.603	2.065
FC 2	0.651	5.812	< 0.001	2.549	5.37	< 0.001	0.423	2.442
FC 3	0.775	8.32	< 0.001	3.899	6.753	< 0.001	0.601	1.602
FC 4	0.822	9.799	< 0.001	2.919	7.369	< 0.001	0.676	1.845
FC 5	0.84	10.519	< 0.001	2.962	8.328	< 0.001	0.706	1.873
FC 6	0.835	10.285	< 0.001	3.024	7.56	< 0.001	0.697	1.995
FC 7	0.784	8.552	< 0.001	3.213	7.102	< 0.001	0.614	1.982
FC 8	0.739	7.437	< 0.001	2.809	5.556	< 0.001	0.546	1.891
LC 1	0.834	10.256	< 0.001	2.937	8.136	< 0.001	0.696	1.869
LC 2	0.809	9.318	< 0.001	3.115	7.921	< 0.001	0.654	2.06
LC 3	0.85	10.926	< 0.001	2.877	8.923	< 0.001	0.722	1.678
LC 4	0.832	10.154	< 0.001	2.507	7.171	< 0.001	0.691	1.872
LC 5	0.832	10.189	< 0.001	2.678	7.495	< 0.001	0.693	1.817
LC 6	0.836	10.348	< 0.001	2.743	7.783	< 0.001	0.699	1.792
LC 7	0.817	9.594	< 0.001	2.535	7.094	< 0.001	0.667	1.866
LC 8	0.834	10.244	< 0.001	2.572	7.563	< 0.001	0.695	1.888

The estimates of D-CAPM reveal that the fund returns are sensitive to market movements during the periods of negative excess returns as indicated by their positive and statistically significant β^D. While examining the D-CAPM estimates of large-cap funds, it can be seen that there is stronger and more stable exposure to downside risk than flexi-cap funds as indicated by their relatively higher and more consistent β^D coefficients. This depicts that large-cap funds tend to move more closely with market even during downturns which is in consistent with their focused selection of market-leading stocks. Relatively lower β^D coefficients of flexi-cap funds reveal that greater benefits and enhanced flexibility existed in asset allocation during market downturns. After controlling the downside risk, they could generate abnormal performance even during adverse market conditions as indicated by the consistently significant α^D. The relatively higher R^2 values of large-cap funds indicate strong explanatory power of the D-CAPM model whereas flexi-cap funds show relatively higher scope for dynamic risk adjustment and managerial choice. Moreover, Durbin-Watson statistics close to zero, indicating the absence of serious auto correlation, support the adequacy and reliability of the D-CAPM model employed in the present study

Table 3: ***Cross Sectional Regression of Downside Beta and Lower Partial Moment***

Predictor	**Coefficient (γ1)**	Standard Error	t- Statistic	p- value	95% confidence interval	
					Lower Bound	Upper Bound
LPM_2	-0.003	0.008	-0.336	0.741	-0.021	0.015

To examine whether LPM_2 explains variations across funds in downside market condition, a cross-sectional regression analysis was carried out. The results of the analysis indicate that LPM_2 does not significantly predicted downside beta. Variations in downside risk measured by LPM_2 are not associated with downside market sensitivity across the selected mutual fund categories as shown by the estimated γ_1 coefficient of LPM_2 which is negative and is statistically insignificant ($p > 0.05$). The model explains a negligible proportion of the variance in β^D with weak explanatory power. Findings of the study reveal that β^D captures dimensions of downside risk which is distinct from LPM based measures.

Table 4: ***Model Fit and Diagnostic Statistics for the D-CAPM***

R	R^2	Adj. R^2	F-Statistic	p-Value	Standard Error
0.09	0.008	-0.063	0.113	0.741	0.053

The model fit and diagnostic statistics reveal that the regression model explaining β^D using LPM_2 exhibits very weak explanatory power. Only 0.8% of the variations in β^D is explained by LPM_2, indicated by the coefficient of determination ($R^2 = .008$). The overall model is statistically insignificant (F 1, 14) = 0.113, p = 0.741). In the present study, second order lower partial moment does not explain downside market sensitivity and β^D is largely not dependent on the lower partial moment.

Table 5: ***Comparison of Downside Risk Between Fund Categories***

Fund Category	Mean LPM_2	SD	SE
Flexi-Cap	6.216	2.014	0.712
Large-cap	4.616	0.393	0.139

The descriptive statistics for LPM_2 across fund categories as presented in Table 5 indicate that flexi-cap funds exhibit greater downside risk exposure with higher mean LPM_2 as compared to large-cap funds. The standard error and standard deviation of the funds suggest moderate dispersion of downside outcomes within each fund category.

Table 6: ***Independent Sample t-Test for Downside Risk Measures across Categories of Funds***

Fund Category Comparison	t- Value	df	p- Value	Mean Difference	95% Confidence Interval	
					Lower	Upper
Flexi-Cap Vs Large-Cap	2.204	7.533	0.061	1.599	-0.093	3.291

To examine whether LPM_2 differed significantly between flexi-cap and large-cap funds, an independent sample *t* test was conducted. Levene's test indicated that the assumption of homogeneity of variances was violated (F 9.861, p = 0.007). Hence, Welch's test was used. The results revealed that the difference in downside risk between Flexi-cap funds (M = 6.216, SD = 2.014) and Large-cap funds (M = 4.616, SD = 0.393) was not statistically significant, t (7.53) = 2.204, p = .061, 95% CI [−0.093, 3.291]. The findings reveal that even though flexi-cap funds exhibit higher downside risk and more exposure loss, the difference between the funds is statistically insignificant at 5% level, indicating that investors in both fund categories experienced broadly similar levels of downside pain when market fall.

The present study examined the empirical evidence on asymmetric risk behaviour and downside risk exposure of the selected flexi-cap and large-cap mutual funds by using monthly negative excess returns for four years. The study focused on negative market conditions and integrated D-CAPM and LPM_2 for assessing the performance of mutual funds during the post-reclassification period of Indian mutual funds. The evidence from downside risk sensitivity and second order lower partial moment shows that flexi-cap funds experienced higher downside risk sensitivity during unfavourable return periods. Compared to flexi-cap funds, large-cap funds exhibited comparatively compressed dispersion in second order lower partial moment with consistent downside behaviour. Downside beta estimates below unity shows that returns are defensive during market downturns. The cross-sectional regression indicates that higher exposure to downside market movements in case of flexi-cap funds does not result in greater realised downside losses. Investors of both the categories of funds experienced similar levels of down side losses even though flexi-cap funds are more sensitive to market downturns.

Conclusion

The present study examined asymmetric asset pricing and downside risk sensitivity, focusing explicitly on negative market conditions, of Indian mutual funds by integrating D-CAPM and LPM_2. The empirical findings indicate that fund return sensitivities are asymmetrically distributed and both the fund categories exhibited significant exposure to market downturns. It further suggests the existence of managerial skill and portfolio construction may contribute to abnormal performance as indicated by the alpha values. The results demonstrate that flexi cap-cap funds exhibited higher average downside risk and the model fit statistics indicate the validity and robustness of the empirical findings.

The empirical findings indicate that downside risk measures capturing distinct risk dimensions of investors are highly relevant; cross-sectional association between asymmetric asset pricing and downside risk sensitivity reinforces the relevance of downside asset pricing frameworks and the inclusion of flexi-cap funds provides timely understandings into the post-reclassification period, constitute the implications of the study.

The analysis is confined to actively managed Indian flexi-cap and large-cap mutual funds based on negative monthly excess returns for the four years from 2021-2025 and it assumed a linear relationship between downside fund and market returns without considering dynamic risk adjustment during extreme market situations. Furthermore, the downside risk measures are subject to the influence of benchmark sensitivity, constitute the limitations of the study.

The present study can be extended to other portfolio categories or higher frequency data. Incorporating conditional asset pricing, time varying models, cross-market comparison and embedding macroeconomic factors into downside risk measures provide the scope for further research.

The present research specifies that the downside risk measures and asymmetric asset pricing models yield richer insights into portfolio evaluation than the conventional symmetrical measures, especially in mutual fund context where the investors are more sensitive to downside deviations. Downside-CAPM and second order lower partial moment together provide more investor centric and realistic research by emphasising that the market efficiency does not preclude meaningful downside exposure during market downturns, contributing meaningfully to asset pricing literature.

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