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Article

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Cogent Economics & Finance

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Suggested Citation: Malhotra, Davinder; Singh, Rahul; Ramani, L. (2024) : Navigating market volatility: risk and return insights from Indian mutual funds, Cogent Economics & Finance, ISSN 2332-2039, Taylor & Francis, Abingdon, Vol. 12, Iss. 1, pp. 1-21, <https://doi.org/10.1080/23322039.2024.2431535>

This Version is available at:

<https://hdl.handle.net/10419/321681>

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To cite this article: Davinder Malhotra, Rahul Singh & L. Ramani (2024) Navigating market volatility: risk and return insights from Indian mutual funds, Cogent Economics & Finance, 12:1, 2431535, DOI: [10.1080/23322039.2024.2431535](https://doi.org/10.1080/23322039.2024.2431535)

To link to this article: <https://doi.org/10.1080/23322039.2024.2431535>



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Navigating market volatility: risk and return insights from Indian mutual funds

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ABSTRACT

This study evaluates Indian mutual funds using a variety of criteria, demonstrating a historical tendency of lower monthly returns and volatility when compared to benchmark indexes. This positive risk profile implies that it will appeal to investors who want stability. Despite COVID-19-induced market volatility, mutual funds persistently outperform benchmark indices in terms of average return per unit of risk, highlighting their potential as a dependable investment option for stability seekers. Furthermore, Indian mutual funds routinely beat benchmark indexes in risk-adjusted terms. Despite having a positive alpha, it lacked statistical significance, indicating a possible reliance on market volatility rather than managerial ability. Notably, while mutual fund managers demonstrated ability in asset selection, they lacked market timing abilities. The study also reveals that Indian mutual funds may demonstrate a considerably reduced downside risk in unfavorable market circumstances than comparable benchmarks.

IMPACT STATEMENT

This study is valuable because it offers a thorough examination of Indian mutual funds, which may reveal a lot about their risk and return characteristics. The study demonstrates how, during difficult periods like the COVID-19 pandemic, these funds with reduced volatility and superior risk-adjusted returns consistently beat indexes. A stability-focused investor may learn about the benefits of Indian mutual funds for stock selection and the fault lines for market timing from this study. By increasing understanding of how mutual funds function in new markets, it provides investors and fund managers with a competitive edge over other investing professionals.

ARTICLE HISTORY

Received 26 July 2024
Revised 4 November 2024
Accepted 14 November 2024

KEYWORDS

Indian mutual funds; Sharpe ratio; Omega ratio; risk-adjusted returns; market timing; security selection

SUBJECTS

Finance; Economics; Business, Management and Accounting

1. Introduction

The mutual funds sector in India is undergoing an impressive transformation, highlighted by a significant increase in assets under management (AUM) and the addition of over 20 million new investment accounts. This surge has resulted in a 19% growth in fund assets during the first 11 months of 2023, placing India ahead of major global counterparts such as the United States, Japan, and China.

Since May 2014, the industry has consistently attracted new investments, leading to a remarkable rise in both AUM and the number of investor accounts. Notably, on 31 May 2014, the AUM surpassed the ₹10 trillion (₹10 lakh crore) mark for the first time. From 31 May 2013 to 31 October 2023, the Indian mutual fund industry's total value skyrocketed from ₹8.68 trillion to ₹46.72 trillion, reflecting an extraordinary fivefold increase over the past decade.

Investor accounts have similarly expanded, with the number of folios increasing from 7.34 crore on 31 May 2018 to 15.96 crore as of 31 October 2023, nearly doubling within five years. Over this period, an average of 13.44 lakh new accounts were established each month. Mutual funds provide a pathway

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for individuals to diversify their portfolios across a range of assets, allowing them to engage in both the Indian equity and bond markets with the aim of achieving favorable financial results.

Considering the remarkable growth of the sector over the past decade, it is essential to evaluate mutual fund performance to assess their impact on the broader economy and financial landscape. The doubling of investor accounts signifies a heightened interest among individual investors in mutual funds in India. By analyzing the performance of different funds, we can gain insights into investor confidence, explore the associated risks and returns, and offer valuable guidance for informed investment decisions.

This research offers an in-depth examination of the performance of Indian mutual funds, highlighting the various factors that impact their results. Our goal is to deliver a thorough analysis of the Indian mutual fund industry and its ability to yield optimal returns by evaluating essential performance indicators, risk assessments, and other pertinent elements.

The study covers a wide range of mutual funds that are currently operating in India. To accurately reflect the industry's plurality and dynamism, we examined funds from a range of asset management firms (AMCs), including both domestic and foreign businesses.

The results of this study not only enhance the existing knowledge on Indian mutual funds but also provide a helpful tool for individual and institutional investors looking to improve their investing choices. Furthermore, asset management businesses and fund managers will get vital knowledge of the advantages and disadvantages of their individual strategies, allowing them to improve and optimize their plans for better overall performance.

The paper is structured as follows: Section II reviews previous studies on mutual fund performance. Section III covers the data utilized. Section IV details the methodology and evaluation models. Empirical results are discussed in Section V. Section VI discusses the directions for future research. Finally, Section VII provides a summary and conclusion.

2. Previous studies

Recently, several studies have analyzed the performance of Indian mutual funds. Suvarna (2022) assessed the efficacy of 52 equity diversified mutual fund schemes in India offered by different providers during the period from April 2009 to March 2019. The study revealed that a considerable proportion of the sampled investment strategies showed positive and statistically significant abilities to choose stocks, while none of them exhibited significantly poor stock selection capabilities. Nevertheless, the study identified a lack of proficiency in the ability to time the market. Hence, the research highlights the significance of improving both the skills of selecting stocks and timing the market in the Indian mutual fund sector to strengthen public confidence. Chauhan et al. (2023) investigated the process by which investors in Indian mutual funds acquire knowledge from previous fund performance and choose how to allocate their cash. Investors prioritize the performance of fund families over individual funds when evaluating their capacity to produce more profits. The study further proposed that this inclination is driven by two factors: the existence of shared abilities within the fund group and adverse connections between fund performance. When the impact of shared capabilities outweighs negative correlations, the performance of the fund-family becomes the main priority. These findings demonstrate how Indian investors utilize the resources of fund families to assess the ability to generate alpha, providing a fresh insight into their learning behavior.

Deb et al. (2007) analyzed the stock selection and market timing abilities of Indian mutual fund managers using both unconditional and conditional methods. Their study of 96 mutual fund schemes indicated that while these managers typically lack effective market timing skills, they excel in stock picking. This conclusion is further supported by pooled regression analyses across various fund categories. Similarly, Pavithra and Kayal (2022) examined market timing capabilities in actively managed Indian mutual funds from 2014 to 2019, finding that value investing had the least style timing, with momentum investing following. In contrast, small-cap funds demonstrated the highest size timing, while multi-cap and large-cap funds showed superior market timing abilities. These findings provide essential insights for fund managers to refine their investment strategies for improved returns.

The study conducted by Agarwal and Pradhan (2019) questioned the conventional method of evaluating mutual fund performance, which heavily relies on the Capital Asset Pricing Model (CAPM) and

assumes a constant level of risk exposure (beta) to the market. The researchers argued that economic conditions can influence this relationship, and therefore proposed a conditional performance evaluation approach that allows for variations in betas and alphas based on changing economic conditions.

The wider body of research about the evaluation of fund performance and the timing of market activities is also relevant. Carhart's (1997) study employed cross-sectional return analysis to assess fund managers' performance, focusing specifically on fund alpha. His primary model incorporates several variables, including the overall market return, size, value (measured by the book-to-market ratio), and one-year momentum. Carhart's findings suggested that mutual fund managers generally lack the necessary expertise and do not possess a distinct informational advantage. According to his four-factor model, the size and momentum factors account for a considerable portion of the variations in returns among mutual funds. Furthermore, his research reveals that commonly referenced attributes, such as turnover, expense ratios, and sales loads—often used by fund managers to signal their expertise—are associated with poorer performance outcomes.

Fama and French (2015) five-factor model extended the Fama and French (1993) three-factor model by integrating the market, size, and value factors, along with additional components intended to capture profitability and investment characteristics. Treynor and Mazuy (1966) assessed fund managers' abilities by introducing a quadratic term into the market model. They argue that managers with effective market timing skills would demonstrate superior performance during strong market conditions and would experience fewer negative returns in weaker years, resulting in a convex relationship in the characteristic line. Gaspar et al. (2006) indicated that mutual fund families frequently function to enhance the collective interests rather than those of individual funds, which may influence both flows and performance.

Henriksson and Merton (1981) introduced and analyzed a model investigating the potential for fund managers to exhibit limited market-timing skills, specifically the ability to predict the direction of excess market returns without accurately forecasting their magnitude. In contrast, Berk and Van Binsbergen (2015, 2016) contend that some fund managers do possess genuine talent. However, they note that in an efficient market, capital tends to flow toward these skilled managers. Furthermore, due to the existence of diseconomies of scale, any demonstrated skill is often offset by fees, leading to a net alpha of zero. Consequently, the authors suggest that the monetary value generated by managers serves as a more reliable measure of expertise within highly efficient financial markets.

Another area of study in performance assessment research highlighted the ever-changing nature of risk premiums and underlines the importance of making modifications that consider information that may accurately anticipate projected returns. Without such adjustments, empirical findings may be deceptive. Ferson and Schadt (1996) contended that market returns may be predicted by observable indicators, such as the market dividend yield, Treasury yields, and yield spreads. As a result, they argued that portfolios created using information that is accessible to the public should not be seen as showing exceptional performance or outcomes driven by expertise. Ferson and Schadt performed calculations of conditional fund alphas, considering conditioning factors such as the market dividend yield and bond market measures, which include Treasury rates and different yield gaps. Their investigation demonstrated that conditional alphas exhibit no persistent deviation from zero. Furthermore, the authors provided data that supports the notion of a substantial lack of skill in market timing, suggesting that funds prefer to take on higher levels of market risk when faced with adverse market returns.

Our analysis is significantly influenced by a variety of studies on risk-adjusted performance, which can be traced back to Sharpe (1964)'s seminal work. In addition to other performance metrics, we implement the Sharpe ratio. The Sortino ratio, which was developed by Sortino and Van Der Meer (1991), simplifies the excess return of an asset over the risk-free rate by dividing it by the asset's adverse deviation. The Sortino Ratio is a relevant performance measure in the context of adverse risk, given the inclinations of investors to avoid risk and loss.

Keating and Shadwick (2002) contend that conventional risk-adjusted performance metrics, which exclusively depend on standard deviations and average returns, have constraints, particularly when returns do not conform to a normal distribution. To resolve this issue, they suggest the Omega ratio, which quantifies the probability-weighted gains and losses associated with an investment. Keating and Shadwick argue that the Omega ratio offers a more comprehensive assessment of an investment's risk and return characteristics due to its inclusion of more than just the first two moments of a return series.

Similarly, Chrétien and Kammoun (2024) compared traditional performance measures to the ‘best clientele alpha’, reflecting mutual funds’ value to favorable investors. They identified two issues: inadmissibility, where alpha exceeds the upper bound, and misrepresentation, where alpha undervalues the fund. Most models misrepresent performance, especially for funds with higher expenses, turnover, longevity, older managers, and smaller net assets. The Managed Portfolio Performance Measure (MPPM) with low-risk aversion best avoids both problems. Furthermore, Abudy, et al. (2024) found that unexpected daily net flows to Israeli government bond mutual funds, held by retail investors, caused significant price changes across bond categories, which reversed within 10 trading days due to ‘price pressure.’ These price distortions also impacted break-even inflation, highlighting that even government bonds are susceptible to retail-driven price effects.

This research contributes to the current body of research by offering a thorough examination of the Indian mutual fund industry. It surpasses the conventional evaluations of performance indicators and risk measures by analyzing a diverse array of influential factors. Our research examines a variety of factors, such as returns, volatility, risk-adjusted returns, benchmarks, fund manager expertise, investment strategies, portfolio composition, and market conditions, by utilizing a combination of quantitative and qualitative methodologies. This comprehensive approach improves our comprehension of the Indian mutual fund landscape and its ability to generate optimal returns.

Our study addresses a significant gap in the existing literature by offering essential information to assist in making financial decisions that align with individual goals and risk tolerances. Moreover, having knowledge about the attributes and factors that influence Indian mutual funds enables participants in the market to effectively navigate, therefore benefiting the broader financial community.

3. Data

The data included in this analysis, pertaining to the monthly performance of mutual funds and benchmark indexes, was obtained from Morningstar Direct. The data for Carhart’s four-factor model was obtained from the Fama-French website. Emerging economies are sometimes considered to be more prone to volatility compared to developed markets, mostly because of reasons such as political instability, currency risk, and the relatively underdeveloped state of their financial systems. When examining equities inside developing economies, the model is adjusted to account for these aspects. The objective of this adaptation is to improve the precision in describing the performance of portfolios that consist of emerging market companies. This undertaking is especially important considering the rising importance of developing economies in the global economy and the increasing interest among investors in these countries. When assessing the performance of Indian mutual funds using multi-factor asset pricing models, we incorporate emerging market characteristics into the model.¹ We utilize three different Indian stock market indexes as mutual fund benchmarks: the FTSE India TR Index, the MSCI India TR Index, and the S&P BSE 500 India TR INR Index. Each of these indexes focuses on various aspects of the Indian equities market. The FTSE India TR INR Index is a broad market index, while the MSCI India NR INR Index concentrates on big and mid-cap firms. The S&P BSE 500 India TR INR Index is a mix of large, mid, and small-cap equities. Combining these indexes ensures a thorough examination of Indian mutual funds across various market categories.

Using several benchmarks enables for a more in-depth analysis of how Indian mutual funds adapt to various investing strategies and risk profiles. The MSCI and FTSE indexes are well-known and utilized by worldwide investors to make allocation choices. By including these indexes, we enable overseas investors to evaluate the performance of Indian mutual funds within the context of their worldwide portfolios.

The S&P BSE 500 India TR INR Index has a greater number of firms, which indicates a wider market breadth. This is especially important for investors who want a more thorough understanding of the Indian stock market. It also enables the evaluation of mutual funds based on their proficiency in navigating a broader array of investment options. Table 1 presents a comprehensive assessment of the absolute return and risk attributes of Indian mutual funds, FTSE India TR Index, MSCI India TR Index, and S&P BSE 500 India TR INR Index. The research utilizes monthly returns data spanning from January 2010 to April 2023, encompassing both the whole period and sub-periods that correspond to economic changes caused by COVID-19.

Table 1. Summary statistics of monthly rates of returns for Indian mutual funds and major indices (January 2010 to April 2023).

	Indian Mutual Funds (%)	FTSE India TR INR (%)	MSCI India NR INR (%)	S&P BSE 500 India TR INR (%)
January 2010 to April 2023				
Mean	0.86	0.95	0.88	1.03
Standard Deviation	3.54	4.82	4.83	5.03
Average return per unit of risk	0.24	0.20	0.18	0.21
February 2020 to January 2021 (COVID-19 lockdown and before vaccinations)				
Mean	1.31	1.86	1.71	1.79
Standard Deviation	7.23	9.57	9.53	10.15
Average return per unit of risk	0.18	0.19	0.18	0.18
February 2021 to April 2023 (Post COVID-19 Vaccination period)				
Mean	1.02	1.13	1.06	1.29
Standard Deviation	2.81	4.09	4.15	4.07
Average return per unit of risk	0.36	0.28	0.26	0.32

Note: This table presents the mean monthly returns, standard deviations, and average returns per unit of risk for Indian Mutual Funds, FTSE India TR INR, MSCI India NR INR, and S&P BSE 500 India TR INR. The analysis is divided into three periods: the overall period from January 2010 to April 2023, the COVID-19 lockdown period from February 2020 to January 2021, and the post-vaccination period from February 2021 to April 2023. The data indicates variations in return and risk across different time frames, highlighting the impact of market conditions on investment performance.

Table 1 shows that based on average monthly returns from January 2010 to April 2023, Indian mutual funds delivered a monthly return of 0.86% with a standard deviation of 3.54%. On the other hand, the average monthly returns of FTSE India TR Index, MSCI India TR Index, and S&P BSE 500 India TR INR Index are 0.95%, 0.88%, and 1.03%, respectively. Indian mutual funds, on average, delivered a lower return relative to benchmark indices, but also carried a lower standard deviation relative to benchmark indices. Therefore, when we compare the average monthly return per unit of risk, mutual funds, on average, outperform FTSE India TR Index, MSCI India TR Index, and S&P BSE 500 India TR INR Index. The average return per unit of risk was mutual funds is 0.24, while the average return for FTSE India TR Index, MSCI India TR Index, and S&P BSE 500 India TR INR Index is 0.20, 0.18, and 0.21, respectively.

The Covid-19 outbreak and subsequent lockdown introduced significant volatility in the stock markets around the World and stock markets around the world declined. We looked at the risk-adjusted performance of Indian mutual funds from February 2020 (when the World Health Organization and the United States declared a public health emergency) through January 2021 (the month when vaccinations started). In terms of absolute performance, the average monthly return of mutual funds at 1.31% is below the average monthly returns of FTSE India TR Index, MSCI India TR Index, and S&P BSE 500 India TR INR Index at 1.86%, 1.71%, and 1.79%, respectively. During this period of global uncertainty and volatility, monthly returns of mutual registered the lowest volatility relative to benchmark indices. Average return per unit of risk for mutual funds is equal to the average monthly returns of MSCI India TR Index, and S&P BSE 500 India TR INR Index at 0.18% and slightly lower than the average monthly return per unit of risk for FTSE India TR Index at 0.19%.

First vaccines for COVID-19 were administered in January 2021 and as markets began to absorb and price the risk of COVID-19, we also analyze the performance of Indian mutual funds relative to benchmark indices. Indian mutual funds during the post vaccination period (February 2021 to April 2023) continue to outperform benchmark indices in terms of average return per unit of risk. The average return per unit of risk for mutual funds is 0.36%, while the average return for FTSE India TR Index, MSCI India TR Index, and S&P BSE 500 India TR INR Index is 0.28%, 0.26%, and 0.32%, respectively during the post-vaccination period.

4. Model

During our evaluation of the risk-adjusted performance of Indian mutual funds, we assessed their performance in relation to a group of benchmarks, which consisted of the FTSE India TR INR Index, MSCI India NR INR Index, and S&P BSE 500 India TR INR Index.

We utilized a wide variety of criteria to evaluate the performance of the mutual funds. The metrics included the Sharpe ratio (1964), the Sortino ratio (Sortino & Van Der Meer, 1991), and the Omega ratio

(Keating & Shadwick, 2002). The research was conducted using monthly returns data from January 2010 to April 2023. In addition, we employed Carhart's four-factor model to ascertain if Indian mutual funds could produce positive alpha.

4.1. Sharpe ratio

While a portfolio may produce higher returns, it might also do so by accepting a greater level of risk. To assess the degree to which an investment rewards its investors for the risk taken, we calculated the Sharpe Ratio (1964). An increasing Sharpe Ratio indicates a greater likelihood of investment success. Sharpe (1964) provides a framework for quantifying the risk premium in relation to the standard deviation of the portfolio's excess returns. As a result, the capital market line serves as a benchmark for performance evaluation. The Sharpe Ratio, the primary risk-adjusted performance measure, assesses the excess return of an investment over the risk-free rate relative to its standard deviation, as illustrated in Equation 1.

$$\text{Sharpe Ratio} = \frac{r_p - r_f}{\sigma_p} \quad (1)$$

In this case, the risk-free rate is denoted by r_f , the portfolio standard deviation by σ_p , and the portfolio return by r_p .

The Sharpe ratio serves as a tool for assessing the performance of an equity investment relative to a risk-free asset, taking into account the additional risk incurred by holding the investment. A negative Sharpe ratio indicates that a risk-free investment would yield a better risk-adjusted return for the investor. Typically, respectable risk-adjusted returns are represented by Sharpe ratios of one or greater.

The Sharpe ratio effectively addresses the challenge of measuring performance across a diverse set of investments, as increased diversification usually leads to a significantly lower standard deviation in portfolio returns. This reduction in standard deviation occurs because the risks associated with individual securities tend to offset one another. As a result, the Sharpe ratio reflects the overall performance of the portfolio, indicating its breadth.

4.2. Sortino ratio

The Sortino ratio is a modification on the Sharpe ratio that differentiates between unfavorable volatility and overall volatility by considering the asset's standard deviation of negative portfolio returns (downside deviation) rather than the total standard deviation of portfolio returns. A greater Sortino ratio, like the Sharpe ratio, indicates stronger portfolio performance. Equation 2 shows the Sortino ratio.

$$\text{Sortino Ratio} = \frac{(R_p - R_f)}{\sigma_d} \quad (2)$$

Where R_p represents the portfolio return, R_f is the risk-free rate of return, and σ_d is the standard deviation of the portfolio's negative returns.

The Sortino ratio emphasizes the adverse risk of a portfolio, as opposed to its overall volatility. The Sortino ratio provides a more precise assessment of risk by specifically accounting for the standard deviation of negative returns. It explicitly evaluates the portfolio's ability to operate in scenarios where negative returns are present. A portfolio that has achieved higher returns while experiencing less adverse risk has a higher Sortino ratio, which suggests superior performance.

4.3. Omega ratio

Keating and Shadwick (2002) developed Omega ratio which offers a quantitative method for assessing the performance of financial assets by comparing the returns they generate to the associated risks. It is defined as the ratio of weighted gains to weighted losses. The predicted returns are divided into two categories by the metric: gains and losses, or returns that exceed (the upside) and fall below (the downside) the anticipated rate. In simplified terms, the Omega ratio is the ratio of positive returns (excellent)

to negative returns (deficient or terrible). Although the Sharpe ratio only encompasses the first two moments of the return distribution (means and variance), the Omega ratio encompasses all moments of the return distribution, thereby providing the investor with information that the Sharpe ratio does not. Equation 3 shows the Omega ratio.

$$\Omega = \frac{\int_r^b (1 - F(x))dx}{\int_a^r F(x)dx} \quad (3)$$

In this context, $F(x)$ denotes the cumulative probability distribution, reflecting the likelihood that a return will fall below a given threshold value r , which is selected by the investor. The variables a and b represent the investment intervals. Essentially, the Omega ratio can be interpreted as the probability of weighted gains divided by the probability of weighted losses beyond this threshold.

4.4. Carhart's four-factor model

The use of factor models in investment analysis provides a systematic framework for a deeper understanding of investment returns. These models break down returns into various components associated with underlying risk factors, including market trends, economic conditions, sector-specific characteristics, and other relevant determinants. By quantifying the relationship between investment returns and these risk factors, factor models offer valuable insights into the fundamental drivers of investment performance.

Alpha is a key quantitative measure in this context, assessing investment performance beyond what can be explained by known risk factors. It represents the value attributable to the investment manager's skill or strategy, highlighting the portion of performance that remains unexplained after accounting for exposure to systematic market or factor-related risks.

The Carhart (1997) four-factor model incorporates four distinct factors: market risk, size, value, and momentum, in contrast to traditional models such as the CAPM and the Fama-French three-factor model. This methodology, which is well-established for the evaluation of conventional financial assets such as stocks, presents challenges when applied to cannabis ETFs due to the industry's distinctive characteristics.

In the context of cannabis, which is renowned for its price volatility, the Carhart four-factor model includes a momentum factor that is particularly pertinent. Four factors contribute to the explanation of stock returns in the Carhart model:

- **MKT (Market Risk):** This factor represents the systematic risk associated with investing in the overall market within the Carhart framework, as it represents the excess return of the market portfolio over the risk-free rate.
- **Size (abbreviated as SMB for Small Minus Big):** SMB measures the historical excess returns of small-cap stocks relative to large-cap stocks. Historically, small-cap stocks have demonstrated superior long-term performance compared to their large-cap counterparts, illustrating the size effect that is observable in stock returns.
- **Value, denoted by HML (High Minus Low),** reflects the historical excess returns of value stocks compared to growth stocks. Typically, value stocks exhibit lower price-to-book ratios, highlighting their tendency to outperform growth stocks over the long term.
- **Momentum (MOM):** MOM is a measure that evaluates the historical excess returns of stocks exhibiting positive price momentum against those with negative price momentum. The momentum effect, observable in stock returns, reflects the tendency for strong recent performers to continue their positive performance in the short term.

The Carhart model is distinguished from the Fama-French three-factor model by the incorporation of the momentum factor, which offers a more comprehensive framework for elucidating the variability in stock returns. The model posits that in addition to market risks, factors such as company size, valuation (value versus growth), and price momentum significantly influence stock returns.

Equation 4 provides the Carhart's four-factor model and is estimated using monthly returns:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_1 \times (R_{m,t} - R_{f,t}) + \beta_2 \times SMB_t + \beta_3 \times HML_t + \beta_4 \times MOM_t + \varepsilon_{i,t} \quad (4)$$

Where $R_{i,t}$ = the percentage return for firm i in month t .

$R_{f,t}$ = the yield on US Treasury bill month t .

$R_{m,t}$ = the return on CRSP value-weighted index for month t .

$(R_{m,t} - R_{f,t})$ = This variable serves to account for the broad risk associated with investments in the stock market.

SMB_t (Small minus Big) = The SMB factor is calculated by subtracting the returns of small-cap stocks from the returns of large-cap stocks for a given month, which represents the actual value of the capitalization factor.

HML_t (High minus Low) = The HML factor is derived by calculating the difference between the returns of value stocks and growth stocks for a given month, representing the value factor. This approach assesses the historical performance disparity between value stocks, characterized by low price-to-book ratios, and growth stocks, which typically have high price-to-book ratios. A positive HML value indicates that stocks classified as value have outperformed those identified as growth.

MOM_t = The momentum factor at time t reflects the performance of stocks that have exhibited strong historical returns. This factor captures the tendency for stocks with recent positive returns to maintain their upward trajectory, while those that have experienced recent declines are likely to continue underperforming.

$\varepsilon_{i,t}$ = an error term.

A positive loading, denoted by a positive slope (β_s), on the SMB factor suggests that small company stocks are responsive to this factor, while larger company stocks typically exhibit a negative loading. In the same vein, a positive estimate of β_v indicates sensitivity to the value factor, while a negative estimate denotes sensitivity to the growth factor. An inclination toward momentum effects would be indicated by a positive weighting on β_m . Ultimately, a positive alpha (α) suggests that the portfolio manager has assumed a higher level of risk, which is indicative of superior performance. This success can be attributed to the fund's exceptional performance, effective timing skills, or proficiency in security selection. In contrast, a negative alpha signifies that the fund's investments have underperformed relative to the expected risk level. Such underperformance may stem from poor security selection or unexpected changes in the prices of the fund's holdings.

The Carhart model, as previously illustrated, includes a momentum factor that is particularly pertinent in the context of emerging markets such as India. Momentum strategies, which involve purchasing assets that have recently performed well, are prevalent in emerging markets, which are distinguished by their price volatility.

4.5. Robustness check

In order to improve the dependability of our results, we include rolling alphas, conditional alphas, and measures of market-timing and selectivity in our examination of Indian mutual funds. These additional assessments are intended to strengthen the reliability of our findings, assuring their validity across different methodological frameworks and contexts. In addition, we assess the potential loss in monthly returns by employing value at risk (VaR) and conditional value at risk (CvaR) models.

4.5.1. Rolling alphas

A common mistake in financial performance evaluation is relying on a single alpha value calculated for the full assessment period. Such a method may overlook the dynamic character of performance, thus obscuring intervals of strong or weak performance. As a result, we compute rolling monthly alphas—a succession of alpha values derived over successive, shortened intervals—to represent the changing nature of investment performance.

Rolling alpha is the process of computing alpha over a series of time frames that typically overlap. This technique allows for a more in-depth analysis of performance evolution, providing insights into how alpha swings with time. Rolling alphas are often calculated over 12-month intervals, with the

window increasing one month at a time. This systematic technique allows for a comprehensive evaluation of performance patterns, permitting the identification of periods of either strong or weak performance in comparison to the benchmark.

The analysis of rolling alphas is useful in recognizing changes in market circumstances and investing strategies. Notably, continuous negative rolling alphas might serve as an early warning indicator, signaling probable problems with the selected investment strategy or managerial ability. Adopting this proactive posture allows for rapid modifications to reduce hazards.

Employing Carhart's 4-factor model, we calculate rolling monthly alphas in this context. In addition to enabling a meaningful comparison with benchmark indices, this provides a comprehensive assessment of performance stability over time.

4.5.2. Conditional factor models

Previous research has explored the effectiveness of managed funds, often utilizing assessments that can introduce bias due to the inherent fluctuations in risk and risk premiums over time. In this context, Ferson and Schadt (1996) proposed a conditional performance measure designed to account for common variance among funds. Their study illustrated that the inclusion of lagged public information variables, such as interest rates and dividend yields—elements recognized for their impact on stock returns—results in more precise evaluations than those derived from conventional methods. These lagged public information indicators offer critical insights and predictive capabilities regarding future market trends, thereby allowing for more informed assessments of fund performance.

To enhance the traditional Jensen (1968) alpha model, Ferson and Schadt integrated a series of lagged public information variables into their estimation of the conditional performance measure. This adaptation facilitates the calculation of α , representing the conditional performance metric. Instead of depending solely on unconditional betas, their approach modifies the fundamental models to encompass time-varying conditional expected returns and betas.

The methodology employs specific instruments, including the three-month Treasury bill rate (TR3M), the term structure slope (SLOPE)—which reflects the yield differential between the 30-year Treasury bond and the three-month Treasury bill—and the corporate bond market quality spread (QS), which is the yield difference between Moody's BAA-rated and AAA-rated corporate bonds. Additionally, the dividend yield on the S&P 500 is incorporated, with all instruments lagged by one month to accurately capture the required temporal dynamics.

The resulting conditional models, detailed in Equation 5, show where $Z_{(j\ t-1)}$ denotes the demeaned values of the unconditional components. By incorporating these lagged public information variables and implementing time-varying conditional measures, this model presents a more robust and accurate framework for assessing the performance of managed funds.

4.5.2.1. Conditional Carhart four-factor model.

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i(R_{m,t} - R_{f,t}) + \delta\{Z_{t-1} \times (R_{m,t} - R_{f,t})\}_2 + \beta_s \times SMB_t + \beta_v \times HML_t + \beta_r \times MOM_t + \varepsilon_{i,t} \quad (5)$$

4.5.3. Mutual fund market timing and selectivity

'Selectivity' is the term generally used to describe the skill of investment managers in choosing assets that would produce anticipated future returns. On the other hand, 'market timing' refers to the capacity of investment managers to modify their portfolio holdings in reaction to changes in the asset portfolio or general market price fluctuations. Previous research (Henriksson & Merton, 1981; Kon & Jen, 1978; Lee & Rahman, 1990; Treynor & Mazuy, 1966) has already investigated the areas of mutual fund market timing and selectivity. These studies repeatedly show that, on the whole, mutual fund managers generally perform poorly in terms of market timing and selectivity. Treynor and Mazuy (1966) incorporated a quadratic term into the Capital Asset Pricing Model (CAPM) to evaluate market timing and selectivity. They utilized an additional CAPM-based model with a quadratic component to evaluate managers' aptitude in forecasting market volatility. The studies conducted by Treynor and Mazuy (1966), Kon and Jen (1978), Henriksson and Merton (1981), and Lee and Rahman (1990) all emphasize the moderate level of performance that mutual fund managers have attained in terms of market timing and selectivity.

This study utilized two models to analyze market selectivity and timing. The fundamental model, proposed by Treynor and Mazuy (1966), enhances the CAPM or market model by incorporating a quadratic component to account for market timing and selectivity. Equation 6 depicts the Treynor and Mazuy model.

$$R_{i,t} - R_{f,t} = \alpha_s + \beta_1(R_{m,t} - R_{f,t}) + \beta_2 \times (R_{m,t} - R_{f,t})^2 + \varepsilon_{i,t} \quad (6)$$

By examining the relationship between the portfolio return and the market return in a non-linear manner, the coefficient β_2 offers insights into the manager's capacity to accurately predict market performance. Exceptional market timing skills are indicated by a positive and statistically significant β_2 , which suggests that the manager can accurately predict market movements. In contrast, a statistically significant negative β_2 indicates a lack of market timing capabilities. It is indicative that the manager is not capable of market timing if β_2 is not greater than 0. Conversely, α_s denotes 'selectivity', which denotes the manager's proficiency in selecting individual securities that outperform the market.

4.5.4. Conditional market timing and selectivity

We evaluate the performance of Indian mutual funds by using conditional market timing and selectivity models in order to further study the securities selection and market timing skills of portfolio managers. Based on data that is readily available to the public, these models seek to determine the managers' abilities in selectivity and market timing. Equation 7, which builds on the methodology of Ferson and Schadt (1996), illustrates the conditional market timing and selectivity of these funds.

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i(R_{m,t} - R_{f,t}) + \delta\{Z_{t-1} \times (R_{m,t} - R_{f,t})\} + \beta_2 \times (R_{m,t} - R_{f,t})^2 + \varepsilon_{i,t} \quad (7)$$

4.5.5. Analysis of downside risk of monthly returns

In finance, two principal risk metrics used to evaluate possible losses in unfavorable market situations are Value at Risk (VaR) and Conditional Value at Risk (CVaR). These indicators provide insights into the negative risks of Indian mutual funds, facilitating the assessment of a fund's performance resilience.

Value at Risk (VaR) quantifies the highest probable loss a portfolio may incur over a certain time frame at a set confidence level. A decreased VaR implies a fund is less susceptible to significant losses, while an elevated VaR signifies more exposure under unfavorable market conditions. By analyzing the Value at Risk (VaR) of mutual funds, investors may discern those with superior risk management and performance consistency, facilitating more educated investing choices.

CVaR, also known as Conditional Value at Risk, goes beyond VaR by indicating the projected size of losses that exceed the VaR limit. CVaR is the loss that may be predicted when losses surpass the VaR threshold. CVaR, like VaR, helps investors assess a mutual fund's potential downside risk. A mutual fund with a lower CVaR suggests that the losses sustained over the VaR threshold are less severe on average, suggesting superior risk management and stronger performance.

5. Empirical results

Our empirical examination of Indian mutual fund performance relative to benchmark indexes began with correlation analysis, risk-adjusted performance assessment, alpha estimates, and other analytical techniques.

5.1. Correlation analysis

Our empirical analysis starts with an examination of the correlation between the average monthly returns of mutual funds and three indices: the FTSE India TR Index, the MSCI India TR Index, and the S&P BSE 500 India TR INR Index. The results of this correlation analysis are presented in Table 2.

Table 2 demonstrates that the monthly returns of mutual funds show a strong correlation with the monthly returns of the FTSE India TR Index, MSCI India TR Index, and S&P BSE 500 India TR INR Index, ranging from 0.95 to 0.99 between January 2010 and April 2023.

Table 2. Correlation among monthly returns of Indian mutual funds and major indices (January 2010 to April 2023).

	Indian Mutual Funds	FTSE India TR INR Index	MSCI India NR INR Index	S&P BSE 500 India TR INR Index
<i>January 2010 to April 2023</i>				
Indian Mutual Funds	1.00			
FTSE India TR INR Index	0.96	1.00		
MSCI India INR Index	0.95	0.99	1.00	
S&P BSE 500 India TR INR Index	0.99	0.99	0.98	1.00
<i>February 2020 to January 2021 (COVID-19 lockdowns and before vaccinations)</i>				
Indian Mutual Funds	1.00			
FTSE India TR INR Index	0.98	1.00		
MSCI India INR Index	0.98	1.00	1.00	
S&P BSE 500 India TR INR Index	1.00	0.99	0.99	1.00
<i>February 2021 to April 2023 (Post-COVID-19 vaccination period)</i>				
Indian Mutual Funds	1.00			
FTSE India TR INR Index	0.96	1.00		
MSCI India INR Index	0.94	0.99	1.00	
S&P BSE 500 India TR INR Index	0.98	0.99	0.98	1.00

Note: This table presents the correlation coefficients among the monthly returns of Indian Mutual Funds, FTSE India TR INR, MSCI India NR INR, and S&P BSE 500 India TR INR for three distinct periods: the overall period from January 2010 to April 2023, the COVID-19 lockdown period from February 2020 to January 2021, and the post-vaccination period from February 2021 to April 2023. Correlation values range from 0 to 1, indicating the strength of the relationship between the returns of the funds and indices, with values closer to 1 reflecting a strong positive correlation.

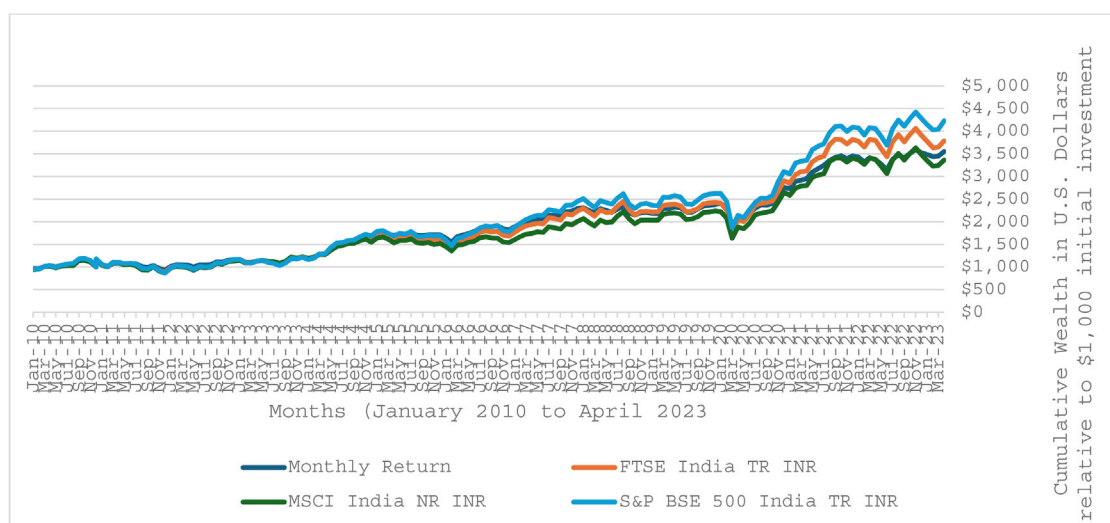


Figure 1. Cumulative wealth effect of investing \$1,000 in an equally-weighted portfolio of mutual funds relative FTSE India Index, MSCI India Index, and S&P 500 India Index. Analysis is based on monthly returns from January 2010 to April 2023.

During the lockdowns prompted by COVID-19, up until the commencement of the first vaccination campaign, the correlation between the average monthly returns of Indian mutual funds and the S&P BSE 500 India TR INR Index reached 1.0. Additionally, the correlations between mutual funds and the FTSE India TR Index and MSCI India TR Index were also notably high at 0.98.

Post COVID-19, the correlation remains high and ranges between 0.94 and 0.98 between the monthly returns of Indian mutual funds, FTSE India TR Index, MSCI India TR Index, and S&P BSE 500 India TR INR Index.

Additionally, we developed a Cumulative Wealth Index (CWI) for Indian mutual funds. Assuming dividend reinvestment, the CWI computes the return on a \$1,000 investment in each category as of January 2010. Furthermore, we calculated a CWI for each of the benchmark indices depicted in Figure 1 to evaluate the cumulative effect of returns over time in relation to an initial investment. The results of a CWI that was developed for each category are depicted in Figure 1.

If we had invested \$1000 in mutual funds in January 2010, it would grow to \$3,550 by April 2023. An investment of \$1000 in FTSE India TR Index in January 2010 would result in an accumulated wealth of \$3.787 at the end of April 2023. On the other hand, an investment of \$1000 in January 2010 in MSCI India TR Index grew to \$3.363 by the end of April 2023. An investment of \$1000 in S&P BSE 500 India TR INR Index in January 2010 grew to \$4,228 at the end of April 2023. Therefore, in absolute terms, S&P BSE 500 India TR INR Index generated more wealth for an investor relative to mutual funds over the period of January 2010 to April 2023. Only MSCI India TR Index underperformed Indian mutual funds.

5.2. Empirical analysis of Sharpe ratio, sortino ratio, and omega ratio

Table 3 displays the findings for the Sharpe ratio, Sortino ratio, and Omega ratio derived from monthly returns spanning January 2010 to April 2023.

Table 3 illustrates that, from January 2010 to April 2023, mutual funds surpassed the FTSE India TR Index, MSCI India TR Index, and S&P BSE 500 India TR INR Index in terms of the Sharpe ratio, Sortino ratio, and Omega ratio. Specifically, Indian mutual funds achieved Sharpe, Sortino, and Omega ratios of 0.23, 0.36, and 1.83, respectively. In comparison, the ratios for the FTSE India TR Index were 0.19, 0.30, and 1.64; for the MSCI India TR Index, they were 0.17, 0.27, and 1.58; and for the S&P BSE 500 India TR INR Index, they were 0.19, 0.31, and 1.68. Thus, mutual funds demonstrated superior risk-adjusted performance compared to the benchmark indices.

During the COVID-19 lockdowns, characterized by global market uncertainty and volatility, mutual funds underperformed relative to the FTSE India TR Index but surpassed the S&P BSE 500 India TR Index. For the period from February 2020 to January 2021, the Sharpe ratio, Sortino ratio, and Omega ratio for mutual funds were 0.18, 0.26, and 1.65, respectively. In contrast, the FTSE India TR Index recorded a Sharpe ratio of 0.19, a Sortino ratio of 0.29, and an Omega ratio of 1.69, all of which were slightly higher than those of Indian mutual funds. Meanwhile, the S&P BSE 500 India TR Index achieved a Sharpe ratio of 0.17, a Sortino ratio of 0.25, and an Omega ratio of 1.61 during the same timeframe, indicating that mutual funds outperformed this benchmark.

5.3. Empirical analysis of multi-factor model

We also compute alpha (α) using four-factor model to analyze the performance of Indian mutual funds relative to benchmark indices. Table 4 summarizes the findings for the four-factor alpha.

Table 3. Risk-adjusted performance metrics for Indian mutual funds and major indices (January 2010 to April 2023).

	Sharpe Ratio	Sortino ratio	Omega ratio
Indian Mutual Funds			
January 2010 to April 2023	0.23	0.36	1.83
February 2020 to January 2021 (COVID-19 lockdowns and before vaccinations)	0.18	0.26	1.65
February 2021 to April 2023 (Post-COVID-19 vaccination period)	0.32	0.64	2.15
FTSE India TR INR index			
January 2010 to April 2023	0.19	0.30	1.64
February 2020 to January 2021 (COVID-19 lockdowns and before vaccinations)	0.19	0.29	1.69
February 2021 to April 2023 (Post-COVID-19 vaccination period)	0.25	0.46	1.83
MSCI India NR INR index			
January 2010 to April 2023	0.17	0.27	1.58
February 2020 to January 2021 (COVID-19 lockdowns and before vaccinations)	0.18	0.27	1.62
February 2021 to April 2023 (Post-COVID-19 vaccination period)	0.23	0.43	1.76
S&P BSE 500 India TR INR index)			
January 2010 to April 2023	0.19	0.31	1.68
February 2020 to January 2021 (COVID-19 lockdowns and before vaccinations)	0.17	0.25	1.61
February 2021 to April 2023 (Post-COVID-19 vaccination period)	0.29	0.57	2.04

Note: This table summarizes the risk-adjusted performance of Indian Mutual Funds, FTSE India TR INR, MSCI India NR INR, and S&P BSE 500 India TR INR, using three key metrics: Sharpe Ratio, Sortino Ratio, and Omega Ratio. The analysis is segmented into three periods: the overall period from January 2010 to April 2023, the COVID-19 lockdown period from February 2020 to January 2021, and the post-vaccination period from February 2021 to April 2023. Sharpe Ratio measures the average return earned in excess of the risk-free rate per unit of volatility (risk). Sortino Ratio is like the Sharpe Ratio but focuses only on downside risk, providing a clearer view of negative volatility. Omega Ratio assesses the likelihood of achieving returns above a certain threshold relative to the likelihood of returns falling below it. Higher values for these ratios indicate better risk-adjusted performance.

Table 4. Monthly net alphas for indian mutual funds based on the Carhart four-factor model (January 2010 to April 2023).

	Net Alpha	Mkt. – RF	SMB	HML	MOM	R ²
January 2010 to April 2023	0.33 (1.48)	0.49 (11.17***)	0.36 (2.60***)	0.36 (3.57***)	0.17 (1.92***)	0.50
February 2020 to January 2021 (COVID-19 lockdowns and before vaccinations)	0.21 (0.47)	0.63 (7.20***)	0.71 (2.71***)	1.09 (2.92**)	0.51 (2.05*)	0.98
February 2021 to April 2023 (Post-COVID-19 vaccination period)	−0.06 (−0.13)	0.53 (4.93***)	0.33 (1.28)	0.55 (3.04***)	0.28 (1.85*)	0.51

***Significant at 1%.

**Significant at 5%.

*Significant at 10%.

Note: This table presents the monthly net alphas for Indian mutual funds as derived from the Carhart four-factor model, which accounts for market return (Mkt – RF), size (SMB), value (HML), and momentum (MOM). The analysis spans three periods: the overall period from January 2010 to April 2023, the COVID-19 lockdown period from February 2020 to January 2021, and the post-vaccination period from February 2021 to April 2023. Net Alpha represents the excess return of the funds after accounting for the risk factors. Mkt – RF (Market Return minus Risk-Free Rate) captures the return attributable to the overall market. SMB (Small Minus Big) measures the size effect, indicating the performance of small-cap stocks relative to large-cap stocks. HML (High Minus Low) reflects the value effect, comparing the performance of high-book-to-market stocks to low-book-to-market stocks. MOM (Momentum) assesses the performance of stocks based on their past returns.

An analysis of monthly returns from January 2010 to April 2023 found that mutual funds had an average positive alpha of 0.33. This positive alpha indicates that these funds beat their predicted returns, implying possibly superior performance. However, it is important to highlight that the positive alpha is not statistically significant. This lack of statistical significance means that the reported outperformance of 0.33 may not be related to the expertise of the fund managers, but rather to random market movements.

The results shown in Table 4 indicate that a substantial portion of the variability in fund returns can be explained by the four-factor model. For Indian mutual funds, the average adjusted R² for the regressions is 0.50. This finding implies that the identified factor exposures related to the equity market in these funds may also capture other systematic factors influenced by changes in the equity market.

When we analyze the four-factor model during COVID-19-induced lockdowns and before the start of vaccinations, Indian mutual funds, on average, delivered a positive alpha although it lacks statistical significance. During the post-vaccination period that runs from February 2021 to April 2023, alpha for Indian mutual funds is again positive and statistically significant. It points to the ability of portfolio managers to generate returns beyond the required return as per the risk.

A close study of the four-factor model shows how important systematic risk is for figuring out mutual fund results. The significance is clear from the beta values, which have a high amount of statistical significance and run from 0.49 to 0.63. These factors clearly show how mutual funds react to changes in the market, which gives us information about how well they are doing. Also, the fact that these factors are very important statistically shows that the model is a good one for understanding why mutual funds make more money than they lose.

Additionally, the robust coefficients on excess market returns provide compelling evidence that Indian mutual fund monthly returns closely mirror the broader market trends. This indicates that mutual funds are heavily influenced by market movements, further emphasizing the importance of systematic risk in their performance.

The presence of a size effect is suggested by the positive and statistically significant coefficient on SMB (Small Minus Big) when the factor models are further examined. In this context, lesser companies typically outperform larger ones. This discovery has significant implications for portfolio construction, as it implies that strategies that prioritize lesser companies may produce advantageous outcomes.

Furthermore, the regression analysis found a positive and statistically significant coefficient on HML (High Minus Low), indicating that mutual funds with a bigger concentration of value stocks perform better. This suggests that value-oriented strategies, which target equities with attractive values, might be beneficial for mutual fund managers seeking greater returns.

Additionally, the positive and statistically significant coefficient on momentum variables provides an additional layer of insight. The momentum factor is beneficial to portfolio returns when it is favorable, signifying that assets with strong recent performance are anticipated to continue performing well. To put it simply, this means that investments that have done well in the past (often called ‘winners’) tend

Table 5. Monthly net alphas for Indian mutual funds and major indices based on the Carhart four-factor model (January 2010 to April 2023).

	Net Alpha			
	Indian mutual funds	FTSE India TR INR index	MSCI India NR INR index	S&P BSE 500 India TR INR index
January 2010 to April 2023	0.33 (1.48)	0.06 (7.88***)	0.16 (0.52)	0.33 (1.03)
February 2020 to January 2021 (COVID-19 lockdowns and before vaccinations)	0.21 (0.47)	0.04 (3.25***)	−0.26 (−0.29)	0.16 (0.22)
February 2021 to April 2023 (Post-COVID-19 vaccination period)	−0.06 (−0.13)	0.14 (4.26***)	−0.45 (−0.63)	−0.29 (−0.41)

***Significant at 1%.

**Significant at 5%;

*Significant at 10%.

Note: This table presents the monthly net alphas for Indian mutual funds, FTSE India TR INR Index, MSCI India NR INR Index, and S&P BSE 500 India TR INR Index as calculated from the Carhart four-factor model. The analysis covers three distinct periods: the overall period from January 2010 to April 2023, the COVID-19 lockdown period from February 2020 to January 2021, and the post-vaccination period from February 2021 to April 2023. Net Alpha reflects the excess return of each fund or index after adjusting for the risk factors including market return ($Mkt - RF$), size (SMB), value (HML), and momentum (MOM).

to produce better returns on average. This finding shows how important momentum tactics are for managing mutual fund portfolios because they can lead to better overall performance.

We also compared the alphas for Indian mutual funds to the alphas for FTSE India TR Index, MSCI India TR Index, and S&P BSE 500 India TR INR Index for the period January 2010 to April 2023 (full sample), COVID-19 (February 2020 to January 2021), and Post COVID-19 (February 2021 to June 2022). Table 5 summarizes the results for the four-factor model.

Table 5 indicates that Indian mutual funds have demonstrated a positive alpha, which implies the possibility of outperformance. Nevertheless, this alpha is not statistically significant, which means that we cannot determine whether it is a result of manager competence or merely market variance. Conversely, the FTSE India TR Index and the S&P BSE 500 India TR INR Index exhibit statistically significant positive alphas at a 10% rejection level. This suggests that these benchmark indices have consistently exceeded expectations, and the likelihood of this outcome being attributable to chance is reduced. On the other hand, the alpha for the MSCI India TR Index is also positive; however, it is not statistically significant, rendering it less reliable as an indicator of performance beyond projections. Consequently, Indian mutual funds did not exhibit a more consistent performance in comparison to benchmark indices on average. The positive alpha for Indian mutual funds may suggest that the management is skilled; however, the lack of statistical significance renders it impossible to determine with certainty. In contrast, the statistically significant positive alphas for the FTSE India TR Index and the S&P BSE 500 India TR INR Index offer more compelling evidence of consistent outperformance, rendering them potentially attractive investments.

Even though the COVID-19 pandemic caused lockdowns, we saw that the alpha of Indian mutual funds stayed positive, which suggests that they might have done better during this tough time. Still, it's important to note that this positive alpha didn't have statistical significance, which means that it's not clear whether it was due to expert knowledge or random changes in the market. Conversely, the FTSE India TR Index produced a statistically significant positive alpha among the lockdowns. These findings indicate that the benchmark index continually exceeded expectations, and the results are sufficiently reliable to have trust in its performance. Like Indian mutual funds, this index also exhibited a positive alpha during the lockdowns. However, similar to mutual funds, this finding lacked statistical significance. This suggests that the apparent superior performance may have been a result of market volatility rather than a dependable sign of performance exceeding expectations. The alpha of the MSCI India TR Index became negative during the lockdowns, indicating that it performed worse than expected. This alpha value was not statistically significant.

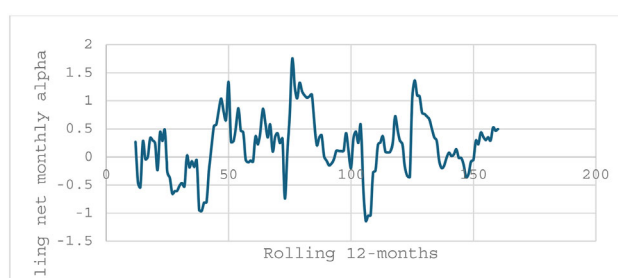
The performance of mutual funds undergoes a significant transformation in the aftermath of the administration of COVID-19 vaccines. The alpha of Indian mutual funds has gone negative, indicating that they are underperforming in comparison to expectations. However, this negative alpha did not demonstrate statistical significance. The FTSE India TR Index is the sole benchmark index that exhibited

Table 6. Summary of average rolling monthly alphas for Indian mutual funds and major indices based on Carhart's four-factor model (January 2010 to April 2023).

	Indian Mutual funds	FTSE India TR INR index	MSCI India INR Index	S&P BSE 500 India TR INR index
Average rolling monthly alpha	0.20	−0.0005	−0.0003	−0.0012
<i>t-statistics</i>				
Average rolling alpha of Indian Mutual Funds versus FTSE India TR INR Index			2.26**	
Average rolling alpha of Indian Mutual Funds versus MSCI India INR Index			2.15**	
Average rolling alpha of Indian Mutual Funds versus S&P 500 India TR INR Index			2.12**	

**Statistically significant at 5% significance level.

Note: This table summarizes the average rolling monthly alphas for Indian mutual funds, FTSE India TR INR Index, MSCI India NR INR Index, and S&P BSE 500 India TR INR Index, calculated using Carhart's four-factor model. The analysis covers the period from January 2010 to April 2023. Average Rolling Monthly Alpha represents the excess return of each fund or index, reflecting their performance after adjusting for risk factors (market return, size, value, and momentum). t-statistics indicate the statistical significance of the difference between the average rolling alpha of Indian mutual funds and each index.

**Figure 2.** Rolling 12-months net monthly alpha for Indian mutual funds based on monthly returns from January 2010 to April 2023.

a positive alpha, which was statistically significant on this occasion. This suggests that the benchmark index persistently exceeded expectations even beyond the immunization period.

5.4. Empirical analysis of rolling alphas

Table 6 presents a summary of the average rolling monthly alphas of mutual funds in comparison to the FTSE India TR Index, MSCI India TR Index, and S&P BSE 500 India TR INR Index.

As shown in Table 6, the average rolling net monthly alpha for Indian mutual funds is 0.20, compared to −0.0005, −0.0003, and −0.0011 for the FTSE India TR Index, MSCI India TR Index, and S&P 500 India TR INR Index, respectively. Notably, the average rolling net monthly alphas for Indian mutual funds show a positive trend and are much greater than those of the benchmark indexes, with the observed differences being statistically significant.

Figure 2 illustrates the distribution of rolling monthly alphas for mutual funds throughout the sample period from January 2010 to August 2022.

As depicted in Figure 2, the distribution of rolling monthly alphas reveals that out of the 149 monthly alphas, 98 are positive, while 51 are negative. The average alpha, standing at 0.20, is found to be statistically significant.

5.5. Empirical analysis of conditional four-factor model

Results for the conditional four-factor models are summarized in Table 7.

Table 7 also demonstrates that when we used publicly accessible information, an equally weighted portfolio of mutual funds had a statistically significant positive alpha of 0.25, which is not statistically significant.

Table 7. Monthly net alphas for Indian Mutual Funds using the conditional Carhart four-factor model (January 2010 to April 2023).

	Conditional Carhart Four Factor Model	
	Net Alpha	R ²
January 2010 to April 2023	0.25 (1.12)	0.53
February 2020 to January 2021 (COVID-19 lockdowns and before vaccinations)	0.70 (0.85)	0.97
February 2021 to April 2023 (Post-COVID-19 vaccination period)	−0.07 (−0.11)	0.41

Note: This table presents the monthly net alphas for Indian mutual funds calculated using the conditional Carhart four-factor model. The analysis spans three periods: the overall period from January 2010 to April 2023, the COVID-19 lockdown period from February 2020 to January 2021, and the post-vaccination period from February 2021 to April 2023. Net Alpha reflects the excess return of the funds after accounting for risk factors, including market return (Mkt – RF), size (SMB), value (HML), and momentum (MOM), while considering the conditional nature of these factors.

Table 8. Summary of results from Treynor and Mazuy (1966) model analysis (January 2010 to April 2023).

Treynor and Mazuy Model			
	α_s	β_2	R ²
January 2010 to April 2023	1.48 (2.56**)	−0.02 (−1.45)	0.16
February 2020 to January 2021 (COVID-19 lockdowns and before vaccinations)	−0.31 (−0.43)	−0.01 (−0.85)	0.94
February 2021 to April 2023 (Post-COVID-19 vaccination period)	1.48 (2.56**)	−0.02 (−1.45)	0.16

***Significant at 1%.

**Significant at 5%.

*Significant at 10%.

Note: This table summarizes the results from the Treynor and Mazuy (1966) model, which assesses fund performance in terms of selectivity and market timing. The analysis covers three periods: the overall period from January 2010 to April 2023, the COVID-19 lockdown period from February 2020 to January 2021, and the post-vaccination period from February 2021 to April 2023. α_s (Selectivity) measures the manager's ability to select securities that outperform the market. β_2 (Market-Timing) indicates the ability of the manager to time the market effectively. T-statistics are provided in parentheses to indicate statistical significance, with the following levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

To explore further into Indian mutual fund performance, we computed conditional alphas based on monthly returns across two time periods. Mutual funds showed a positive alpha from February 2020 to January 2021, indicating probable outperformance. However, this positive alpha lacked statistical significance, so we can't say whether the outperformance was attributable to talent or random market swings. This casts doubt on the veracity of the apparent outperformance during this period.

Mutual funds showed a negative alpha following COVID immunization. Again, like the previous time, this negative alpha was not statistically significant. This suggests that the underperformance noticed during this phase may not be consistent or statistically significant.

These findings underline that, while there were instances of apparent outperformance and underperformance in the two time periods studied, statistical significance is critical in validating the trustworthiness of such observations. The lack of statistical significance emphasizes the need for care in reaching clear conclusions regarding the causes of these performance patterns.

5.6. Empirical analysis of market timing and selectivity

We also assessed the market timing and security selection abilities of Indian mutual fund portfolio managers. The outcomes of this analysis are presented in Table 8, offering insights into the managers' effectiveness in timing the market and selecting securities.

The findings presented in Table 8 indicate that the alpha for Indian mutual funds during the sample period of January 2010 to April 2023 was positive and statistically significant when analyzed using Treynor and Mazuy (1966) model. A positive and statistically significant alpha would have suggested excellent security selection skills on the part of Indian mutual fund portfolio managers.

The coefficient on β_2 , which represents the market timing component, is negative and statistically insignificant. This implies that the portfolio managers did not exhibit significant market timing skills during the analyzed period. Market timing skills would have been indicated by a positive and statistically significant coefficient on β_2 .

Table 9. Summary of results from the conditional Treynor and Mazuy (1966) model analysis (January 2010 to April 2023).

Treynor and Mazuyi model			
	α_s	β_2	R ²
January 2010 to April 2023	0.74 (3.16***)	−0.01 (−1.62)	0.49
February 2020 to January 2021 (COVID-19 lockdowns and before vaccinations)	−0.33 (−0.38)	0.01 (0.23)	0.94
February 2021 to April 2023 (Post-COVID-19 vaccination period)	1.53 (2.43**)	−0.01 (−0.85)	0.15

Significant at 1%, **Significant at 5%, *Significant at 10%.

Note: This table summarizes the results from the conditional Treynor and Mazuy (1966) model, which evaluates fund performance in terms of selectivity and market timing under varying conditions. The analysis spans three periods: the overall period from January 2010 to April 2023, the COVID-19 lockdown period from February 2020 to January 2021, and the post-vaccination period from February 2021 to April 2023.

α_s (Selectivity) measures the manager's ability to select investments that outperform the market. β_2 (Market-Timing) assesses the effectiveness of the manager in timing the market. R² indicates the proportion of variance in fund returns explained by the model. T-statistics are included in parentheses to denote statistical significance, with the following levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 10. Value at risk (VaR) and conditional value at risk (CvaR) for Indian mutual funds and key market indices.

	Indian Mutual funds	FTSE India TR INR index	MSCI India INR Index	S&P BSE 500 India TR INR Index
Value at risk at 95% confidence interval	−4.20	−5.74	−5.81	−6.13
Conditional value at risk (CvaR)	−7.20	−9.46	−9.60	−10.26

Note: This table presents the Value at Risk (VaR) and Conditional Value at Risk (CvaR) for selected Indian mutual funds and major equity indices, including the FTSE India Total Return Index (TR INR), MSCI India Total Return Index (INR), and S&P BSE 500 Total Return Index (TR INR). The analysis is based on monthly returns from January 2010 to April 2023. VaR is calculated at a 95% confidence level, indicating the potential loss in value of an investment over a specified time period under normal market conditions. CvaR represents the expected loss exceeding the VaR threshold.

During the COVID-19-induced lockdowns, Indian mutual funds delivered a negative alpha, but it was not statistically significant. This suggests that while there may have been some potential for generating excess returns during this period, the observed underperformance could be attributed to random chance rather than skillful security selection. Post COVID-19 vaccination period shows that the alpha is positive and statistically significant, attesting to the security selection abilities of fund managers in the Indian market.

Overall, the results from Table 7 indicate that portfolio managers did exhibit significant security selection or market timing skills during the analyzed period, based on the Treynor and Mazuy (1966) model.

Results of the conditional market timing and selectivity model are summarized in Table 9.

The results of the conditional Treynor and Mazuy (1966) model indicate a positive and statistically significant alpha. Additionally, β_2 is negative but not statistically significant, suggesting that the portfolio managers did demonstrate superior security selection expertise when utilizing publicly available information.

5.7. Empirical analysis of downside risk

The results in Table 10, which display Value at Risk (VaR) and Conditional Value at Risk (CvaR) metrics for various financial instruments and indices, provide insights into their risk exposure during the period from January 2010 to April 2023.

Value at Risk (VaR) at the 95% confidence level is the upper limit of the projected loss for a certain time (monthly, in this instance) assuming normal market circumstances. For example, if the Value at Risk (VaR) for Indian Mutual Funds is −4.20%, it means that there is a 5% chance that their monthly losses might be greater than this percentage. Similarly, the higher values of Value at Risk (VaR) for other indices such as FTSE India TR INR Index (−5.74%), MSCI India INR Index (−5.81%), and S&P BSE 500 India TR INR Index (−6.13%) suggest that these indices may experience larger losses compared to Indian Mutual Funds.

Conditional Value at Risk (CvaR), often referred to as Expected Shortfall, expands on the concept of VaR by measuring the anticipated loss beyond the VaR threshold in unfavorable market situations. A CvaR of −7.20% for Indian Mutual Funds indicates that when losses above the VaR threshold of −4.20%,

the anticipated average loss might go as high as -7.20% . Similarly, the higher CvaR readings (-9.46% , -9.60% , -10.26%) for other indices indicate a greater likelihood of experiencing significant losses under extreme market situations that go beyond their respective VaR thresholds. This suggests that Indian mutual funds have a comparatively lower level of risk in unfavorable market situations when compared to comparable benchmarks.

6. Directions for future research

The findings of this study could be further developed through future research in several critical areas. One potential approach is to investigate the influence of environmental, social, and governance (ESG) factors on Indian mutual funds. Valuable insights may be gained by comprehending the way these factors affect fund performance, as investors prioritize ESG criteria.

Furthermore, the performance of sector-specific mutual funds, such as those that concentrate on technology or healthcare, could be more thoroughly evaluated to evaluate their growth potential or resilience during economic fluctuations. An additional potential research area is the examination of the performance of fund families.

An additional extension of this study could involve a family-level analysis to assess the impact of mutual fund families on performance and fund flow along the lines of by Gaspar et al. (2006). Future research may explore whether funds within the same family demonstrate unique performance trends or possess advantages that differentiate them from independent funds.

Future studies may explore the impact of family-level strategies, such as cross-subsidization—shifting assets between funds within the same family to temporarily enhance the performance of certain funds—and investigate whether these practices influence investor fund flows.

Lastly, the integration of a behavioral finance perspective could provide insight into the ways in which investor sentiment, biases, and behavior influence mutual fund inflows and performance, particularly in volatile markets.

7. Summary and conclusions

The Indian mutual fund industry has experienced substantial growth in recent years, with assets under management (AUM) increasing by fivefold over the past decade. The mutual funds industry's expansion may be attributed to a variety of factors, including the implementation of regulatory reforms that have facilitated the access of investors to mutual funds, the increased participation of retail investors, and the development of new products and services.

This study evaluated the overall and risk-adjusted performance of Indian mutual funds using several quantitative techniques. Indian mutual funds have exhibited monthly returns in their past performance that, although frequently lower when compared to benchmark indexes, have been accompanied by the advantage of less volatility. The diminished risk profile of mutual funds is a notable benefit, which might make them an attractive option for investors who prefer stability in their investing portfolios.

Amidst the market volatility triggered by COVID-19 and subsequent immunization efforts, Indian mutual funds have consistently demonstrated their capacity to outperform benchmark indexes in terms of average risk-adjusted returns. Mutual funds have consistently rebounded during challenging periods, making them a potentially reliable choice for investors seeking stability.

The findings suggest that Indian mutual funds provide superior risk-adjusted returns in comparison to their benchmarks. This is of particular importance to investors. This makes mutual funds an appealing option for investors who are risk-averse and seek consistent returns. While acknowledging the importance of improving market timing strategies to enhance overall performance, fund managers can leverage the assets they have identified in stock selection and capitalize on them. Furthermore, investors who are interested in optimizing their portfolios to mitigate downside risk may find the information concerning the resilience of mutual funds during crises to be advantageous.

The study contributes to the growing body of literature on mutual fund performance in emerging markets. By confirming previous findings on the stock selection abilities of Indian mutual fund managers and using multi-factor models to evaluate performance during significant global events, this research

expands the theoretical understanding of how mutual funds behave during the crisis period. The use of rolling alphas and conditional models introduces a dynamic perspective to the evaluation of mutual funds, offering a more nuanced understanding of fund performance over time.

Our results align with prior research on Indian mutual funds, indicating that fund managers exhibit robust stock-picking skills but exhibit limited market timing capabilities. Suvarna (2022) and Deb et al. (2007) have highlighted these trends, and our findings corroborate their conclusions. We advance this notion by using Carhart's four-factor model to assess the performance of mutual funds during volatile times, including the COVID-19 pandemic. Indian mutual funds surpass benchmarks in risk-adjusted returns, especially in volatile markets, as shown by our study, aligning with the findings of Chauhan et al. (2023) and Choudhary and Chawla (2016). We enhance the literature about mutual funds' reactions to global events by examining rolling alphas and conditional models, yielding novel insights into post-pandemic recovery. Additionally, our research examined the downside risk of monthly returns of Indian mutual funds in comparison to benchmark indexes.

Note

1. The emerging markets countries currently include:

Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Malaysia, Mexico, Pakistan, Peru, Philippines, Poland, Qatar, Saudi Arabia, South Africa, South Korea, Taiwan, Thailand, Turkey, United Arab Emirates.

Authors' contributions

Conceptualization: Davinder Malhotra, Rahul Singh, and L. Ramani. Data curation: Davinder Malhotra, Rahul Singh, and L. Ramani. Funding acquisition: Not Applicable. Investigation: Davinder Malhotra, Rahul Singh, and L. Ramani. Methodology: Davinder Malhotra, Rahul Singh, and L. Ramani. Project administration: Davinder Malhotra, Rahul Singh, and L. Ramani. Resources: Not Applicable. Software: Davinder Malhotra, Rahul Singh, and L. Ramani. Supervision: Davinder Malhotra, Rahul Singh, and L. Ramani. Validation: Davinder Malhotra, Rahul Singh, and L. Ramani. Writing – original draft: Davinder Malhotra. Writing – reviewing & editing: Davinder Malhotra, Rahul Singh, and L. Ramani. All authors have read and approved the final version of the manuscript.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

No funding was received for this research.

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Data availability statement

We are not allowed to provide data as per our agreement with the data provider, but portions of data and materials supporting the results of this study are available upon request. Furthermore, requests for data access should be directed to Davinder Malhotra ( Davinder.Malhotra@Jefferson.edu).

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