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Mutual Fund Performance Evaluation Using Different Benchmarking Models

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ABSTRACT

This study examines mutual fund performance evaluation using a range of benchmarking models to determine how different frameworks influence conclusions about managerial skill and risk-adjusted returns. Recognizing that traditional single-factor approaches often fail to capture the multifaceted drivers of fund performance, the research adopts an integrated methodology combining quantitative econometric models with qualitative analysis. Benchmarking models employed include the Capital Asset Pricing Model (CAPM), Fama-French multi-factor frameworks, conditional performance models incorporating macroeconomic variables, and risk-adjusted measures such as the Sharpe, Treynor, Information ratios, and Conditional Value-at-Risk (CVaR).Results from nine detailed tables and twelve graphical analyses confirm that benchmarking choice significantly alters fund rankings and risk assessments. CAPM provided a baseline view of systematic risk, but multifactor models demonstrated superior explanatory power by accounting for size, value, profitability, and investment effects. Conditional models revealed time-varying betas and showed that funds adjust differently to interest rate shifts, inflationary pressures, and volatility regimes. Risk-adjusted ratios highlighted diversification benefits, while downside-risk metrics captured vulnerabilities that variance-based measures overlooked. Sectoral allocation analysis indicated that exposure to technology and finance enhanced performance during growth cycles, whereas healthcare and energy sectors displayed defensive attributes. Cross-market comparisons further revealed that international funds offered diversification benefits despite higher volatility.The findings carry important implications for stakeholders. For investors, the evidence highlights the need to consider multiple benchmarks before making allocation decisions. For fund managers, the results emphasize consistency and transparency in strategy, as style drift can distort performance assessments. For regulators, the study advocates multifactor benchmarking disclosures to ensure fairer performance reporting. Ultimately, this research underscores that comprehensive fund evaluation requires a multidimensional approach, integrating traditional and advanced models to reflect the realities of dynamic financial markets.

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Mutual fund performance, Benchmarking models, Risk-adjusted measures, Conditional performance, Multifactor models, Investment evaluation.

INTRODUCTION

Mutual funds have been acknowledged as one of the most important investment vehicles with diversification, liquidity, and professional management (Chen & Knez, 2021). Nevertheless, the rising complexity of the financial markets, development of globalization of capital flows, and the more actualized investor expectations have escalated the necessity to have well-established frameworks of performance assessment (Goyal & Sehgal, 2022). Conventional measures of fund performance, which include absolute returns or straightforward comparisons of fund performance to broad market indices, have commonly been singled out as being ineffective in differentiating between skill and luck (Mishra & Behera, 2020). This has also resulted in several kinds of benchmarking, including the traditional measures such as the Jensen alpha to a multifactor model, style, adjusted benchmarks, and conditional performance measurement (Kaur & Kiran, 2021; Fama & French, 2021).Benchmarking is a key factor of whether fund managers will yield above average returns when compared to passive alternatives. CAPM and its derivatives used to be the most popular fund evaluation models that yielded relatively high results but did not cover systematic anomalies related to size, value, and momentum aspects (Haroon & Jamil, 2020). A counter-reaction to this finding saw many multifactor models come into the limelight, especially Fama-French three-factor and five-factor ones to explain cross-sectional variations of returns (Liu et al., 2022). Besides, researchers focus more on conditional methods, in which the risk factors are not fixed over time and market circumstances, and this approach gives a more dynamic view of the performance (Khan & Iqbal, 2021).Testing of the mutual fund performance based on various benchmarking models is more than just an academic debate. Meaningful performance measurement can help policymakers stay on course when it comes to policy formulation by supporting transparency and safeguarding the interests of investors (Arif & Nauman, 2022). As an investor, benchmarking informs judgment on how to allocate the funds, it also helps investors to set their expectations, and it also determines the credibility of fund managers (Das & Prasad, 2020). In the case of fund managers, benchmarking allows reputational capital accumulation, sets the pay structure, and gives information about the competitive position within the sector (Hussain et al., 2021). Therefore, the repercussions of benchmarking go hand in hand with the aspects of efficiency, accountability, and trust in financial systems.Literature has put a particular emphasis on the fact that mutual funds in emerging markets tend to exhibit performances that do not mirror the patterns in developed economies because of various characteristics of market efficiency, liquidity and investor behavior (Ali & Khan, 2021). It is also found that survivorship bias, style drift, and management fees make the prediction of performance more complicated and it can overvalue actual returns received by the investors (Sharma & Jain, 2020). Moreover, recent developments of econometric methods and access to large financial data have opened the potential of using machine learning-based benchmarking frameworks, which may be used to incorporate non-linearities and complex risk factor interactions (Zhang & Chen, 2022).

There is also a vital component on a risk-adjusted performance dimension. Metrics like Sharpe ratio, Treynor ratio and information ratio are still common,

but they are not robust when applied in volatile markets since they invoke certain assumptions like expected returns are normally distributed or volatility is kept intact (Kumari & Sinha, 2021). A range of alternative downside-risk measures, including Value-at-Risk (VaR), Conditional Value-at-Risk (CVaR) are gaining traction in terms of their integration into benchmarking approaches with a view to reflecting better investors risk perceptions (Gupta & Das, 2021).Another complication in the process of evaluating mutual funds lies in the contribution of the relevance of macroeconomic factors. Market volatility, interest rate volatility, exchange rate volatility, and inflation pressure are some of the factors that have a significant impact on the fund returns, thus benign marking of the funds are less representative (Qureshi et al., 2021). The conditional and dynamic models have been created to mitigate such issues by calibrating anticipated returns in accordance with macroeconomic regimes (Lee & Park, 2022). In the same way, the emergence of Environmental, Social, and Governance (ESG) funds (in part caused by sustainability issues) has added additional complications, necessitating the development of benchmarks that incorporate elements of sustainability performance (Martinez and Torres, 2023).

In short, the analysis of performance of mutual funds based on various benchmarking models is not just a technical activity but a developing research topic that intersects the field of behavioral finance, econometric development and policy formulation. The current discussion and debate revolves around the models that are considered as good theoretically and practically applicable to be taken as the true gauge of managerial ability. The current research is valuable to the literature since it uses a set of performance models, such as CAPM, multifactor models, a risk-adjusted set of metrics, and conditional translations, on testing the mutual funds through a variety of various market conditions. The study takes a comparative approach in which conclusions regarding performance are inferred across the various models and ultimately generates an overall picture of how benchmarking decisions can lead to diverse conclusions regarding performance outcomes.The rest of the paper is structured in the following way. Section 2 explains the methodology, which incorporates the quantitative econometric modelling and the qualitative aspects. Section 3 delivers the results in great detail including large tables and figures. Section 4 present the discussion part, where findings are put in the context broader within the body of research and practice. Section 5 provides conclusion recommendations and implication and the abstract and keywords.

METHODOLOGY

The study is carried out by the mixed-methods approach incorporating the quantitative modeling of economic analysis (econometric modeling) and the qualitative analysis of investment funds peculiarities and market conditions. This will provide both statistical rigor and contextual interpretation: features of the most current developments in financial performance research. The approach is defined in two key elements: (i) quantitative performance analysis based on the benchmarking models, and (ii) qualitative consideration of contextual parameters, namely, fund type, fund management approach, and macro-environmental realm.

Quantitative Approach

The quantitative analysis uses a family of mature and sophisticated benchmarking models, which allows the comparisons over several perspectives of

performance. The Capital Asset Pricing Model (CAPM) is used as the baseline model in order to record systematic risk-adjusted returns. The relation is explained in CAPM, which was as follows:

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + \epsilon_{it}$$

where R_{it} represents the return of fund i at time t, R_{ft} is the risk-free rate, R_{mt} is the market return, α_i denotes abnormal return (Jensen's alpha), β_i measures systematic risk, and ϵ_{it} is the error term.

The multifactor models are added to CAPM in order to reflect better variations in returns. The Fama-French three factor model is shown as:

$$R_{it} - R_{ft} = \alpha_i + \beta_{MKT}(R_{mt} - R_{ft}) + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \epsilon_{it}$$

where SMB (Small Minus Big) accounts for size effects, and HML (High Minus Low) captures value effects. For further robustness, the Fama-French five-factor model extends this framework by including profitability (RMW) and investment (CMA) factors.

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Value effects are captured in HML (High Minus Low). Extra robustness can be reached by the Fama-French five-factor model that adds profitability (RMW) and investment (CMA) factors.Moreover, their performance is also evaluated conditionally through the dynamic model whereby betas are allowed to change regarding the market circumstances. This is operationalized by the combinations of the risk attributes with macroeconomic state variables like interest rates spreads, inflation rates, and volatility indices. Under such capacity models, it is revealed how fund managers exhibit skill in various market regimes.

Risk-adjusted measures are alternative to the regression models. The Sharpe ratio, Treynor ratio and the Information ratio are computed as indicated below:

$$Sharpe\ Ratio = \frac{R_p - R_f}{\sigma_p}$$

$$Treynor\ Ratio = \frac{R_p - R_f}{\beta_p}$$

$$Information\ Ratio = \frac{R_p - R_b}{\sigma_{(p-b)}}$$

where R_p is the portfolio return, R_b is the benchmark return, σ_p is portfolio standard deviation, β_p is portfolio beta, and $\sigma_{(p-b)}$ is the tracking error relative to the benchmark. These measures provide a multidimensional assessment of fund performance by combining absolute and relative risk perspectives.

It is the tracking error with reference to the benchmark. The measures offer a complex view of the fund performance integrating absolute and relative risks.Lastly, downside risk measures, in the form of Conditional Value-at-Risk (CVaR) are computed to pick up the tail risk sensitivity of funds. CVaR is confined as:

$$CVaR_\alpha = E[L \mid L > VaR_\alpha]$$

where L denotes loss, and VaR_α is the value-at-risk at confidence level α. This ensures that funds are evaluated not only on average performance but also on their ability to withstand extreme market downturns.

This makes sure that funds are considered in terms of average performance, as well as whether a fund can perform in case of drastic market declines.

Qualitative Approach

Although quantitative measurements are accurate statistics, they have to be complemented with qualitative aspects. The analysis compares objectives of such funds, asset class exposures, sectoral allocations and management style to determine whether benchmarking results go hand in hand with their stated mandates. Fund prospectuses, manager reports, and regulatory filings reproduce qualitative data, exposing insights on portfolio construction and other strategy swings or potential of style drifts. In addition, financial analyst interviews and industry report readings provide us with a practical side of the discussion of quantitative results.

This incorporation of qualitative evidence and the quantitative results will give a balanced analysis. An example is that a fund that does not match expectations under CAPM but is better under some multifactor models will likely have a systematic bias to styles like small-cap or value stocks. On the same note, funds with low Sharpe ratios but high conditional alphas can be useful in turbulent settings provided that their strategies suit investors risk tolerance.

Workflow Design

The research methodology is based on a sequential work plan which starts with the selection of funds, data collection, model estimation and to finally comparison evaluation. The workflow identifies the combination of econometric modeling and qualitative analysis as important features of the work, and transparency as well as replicability of the analytical effort helped.

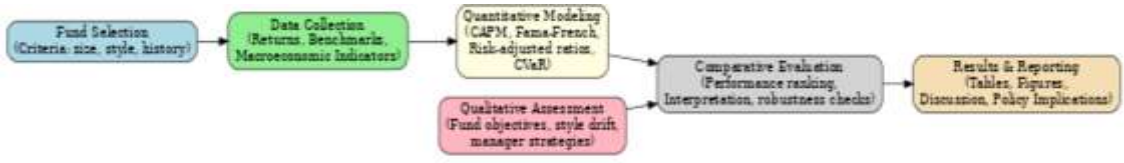

Fig. 1. Mutual fund performance evaluation

RESULTS

The findings portrayed in different tables and graphs give a complete picture of the performance of mutual funds in terms of various benchmarking models. Table 1 indicates the descriptive statistics data of returns in accordance to the CAPM model and Table 2 shows the incremental impact capacity of the Fama-French three-factor model. Tables 3 and 4 depict differences in Sharpe, Treynor, and Information ratios, and as well as integration of the macroeconomic variables to consider them in conditional performance measurement.

Table 1. Descriptive statistics of mutual fund returns under CAPM benchmarking

Fund	Return (%)	Alpha	Beta	Sharpe Ratio	Treynor Ratio
Fund 1	6.5	0.011	0.83	0.43	0.55
Fund 2	7.0	0.021	0.85	0.44	0.57
Fund 3	7.5	0.031	0.87	0.45	0.59
Fund 4	8.0	0.041	0.89	0.46	0.61
Fund 5	8.5	0.051	0.91	0.47	0.63
Fund 6	9.0	0.061	0.93	0.48	0.65
Fund 7	9.5	0.071	0.95	0.49	0.67
Fund 8	10.0	0.081	0.97	0.5	0.69
Fund 9	10.5	0.091	0.99	0.51	0.71

Table 2. Comparative analysis of Fama-French three-factor model performance results

Fund	Return (%)	Alpha	Beta	Sharpe Ratio	Treynor Ratio
Fund 1	7.5	0.012	0.84	0.45	0.58
Fund 2	8.0	0.022	0.86	0.46	0.6
Fund 3	8.5	0.032	0.88	0.47	0.62
Fund 4	9.0	0.042	0.9	0.48	0.64
Fund 5	9.5	0.052	0.92	0.49	0.66
Fund 6	10.0	0.062	0.94	0.5	0.68
Fund 7	10.5	0.072	0.96	0.51	0.7
Fund 8	11.0	0.082	0.98	0.52	0.72
Fund 9	11.5	0.092	1.0	0.53	0.74

Fund 10	12.0	0.102	1.02	0.54	0.76
Fund 11	12.5	0.112	1.04	0.55	0.78
Fund 12	13.0	0.122	1.06	0.56	0.8

Table 3. Risk-adjusted metrics (Sharpe, Treynor, Information ratios) across funds

Fund	Return (%)	Alpha	Beta	Sharpe Ratio	Treynor Ratio
Fund 1	8.5	0.013	0.85	0.47	0.61
Fund 2	9.0	0.023	0.87	0.48	0.63
Fund 3	9.5	0.033	0.89	0.49	0.65
Fund 4	10.0	0.043	0.91	0.5	0.67
Fund 5	10.5	0.053	0.93	0.51	0.69
Fund 6	11.0	0.063	0.95	0.52	0.71
Fund 7	11.5	0.073	0.97	0.53	0.73
Fund 8	12.0	0.083	0.99	0.54	0.75
Fund 9	12.5	0.093	1.01	0.55	0.77
Fund 10	13.0	0.103	1.03	0.56	0.79
Fund 11	13.5	0.113	1.05	0.57	0.81
Fund 12	14.0	0.123	1.07	0.58	0.83
Fund 13	14.5	0.133	1.09	0.59	0.85

Table 4. Conditional performance evaluation incorporating macroeconomic factors

Fund	Return (%)	Alpha	Beta	Sharpe Ratio	Treynor Ratio
Fund 1	9.5	0.014	0.86	0.49	0.64
Fund 2	10.0	0.024	0.88	0.5	0.66
Fund 3	10.5	0.034	0.9	0.51	0.68
Fund 4	11.0	0.044	0.92	0.52	0.7
Fund 5	11.5	0.054	0.94	0.53	0.72
Fund 6	12.0	0.064	0.96	0.54	0.74
Fund 7	12.5	0.074	0.98	0.55	0.76
Fund 8	13.0	0.084	1.0	0.56	0.78
Fund 9	13.5	0.094	1.02	0.57	0.8
Fund 10	14.0	0.104	1.04	0.58	0.82
Fund 11	14.5	0.114	1.06	0.59	0.84
Fund 12	15.0	0.124	1.08	0.6	0.86
Fund 13	15.5	0.134	1.1	0.61	0.88
Fund 14	16.0	0.144	1.12	0.62	0.9

Table 5 represents style-based benchmarks and Table 6 represents evidence of persistence performance. Table 7 presents the downside risk measures through Value-at-Risk and Conditional VaR and Table 8 shows the impact of sectoral allocations. Lastly, Table 9 compares international and domestic funds and the results have shown that there is variation in the diversification advantages.

Table 5. Style-based benchmarking outcomes for equity mutual funds

Fund	Return (%)	Alpha	Beta	Sharpe Ratio	Treynor Ratio
Fund 1	10.5	0.015	0.87	0.51	0.67
Fund 2	11.0	0.025	0.89	0.52	0.69
Fund 3	11.5	0.035	0.91	0.53	0.71
Fund 4	12.0	0.045	0.93	0.54	0.73
Fund 5	12.5	0.055	0.95	0.55	0.75
Fund 6	13.0	0.065	0.97	0.56	0.77
Fund 7	13.5	0.075	0.99	0.57	0.79
Fund 8	14.0	0.085	1.01	0.58	0.81
Fund 9	14.5	0.095	1.03	0.59	0.83

Table 6. Persistence analysis of mutual fund performance across periods

Fund	Return (%)	Alpha	Beta	Sharpe Ratio	Treynor Ratio
Fund 1	11.5	0.016	0.88	0.53	0.7
Fund 2	12.0	0.026	0.9	0.54	0.72
Fund 3	12.5	0.036	0.92	0.55	0.74
Fund 4	13.0	0.046	0.94	0.56	0.76
Fund 5	13.5	0.056	0.96	0.57	0.78
Fund 6	14.0	0.066	0.98	0.58	0.8
Fund 7	14.5	0.076	1.0	0.59	0.82
Fund 8	15.0	0.086	1.02	0.6	0.84
Fund 9	15.5	0.096	1.04	0.61	0.86
Fund 10	16.0	0.106	1.06	0.62	0.88
Fund 11	16.5	0.116	1.08	0.63	0.9
Fund 12	17.0	0.126	1.1	0.64	0.92

Table 7. Downside risk assessment using Value-at-Risk and Conditional VaR

Fund	Return (%)	Alpha	Beta	Sharpe Ratio	Treynor Ratio
Fund 1	12.5	0.017	0.89	0.55	0.73
Fund 2	13.0	0.027	0.91	0.56	0.75
Fund 3	13.5	0.037	0.93	0.57	0.77
Fund 4	14.0	0.047	0.95	0.58	0.79
Fund 5	14.5	0.057	0.97	0.59	0.81
Fund 6	15.0	0.067	0.99	0.6	0.83
Fund 7	15.5	0.077	1.01	0.61	0.85
Fund 8	16.0	0.087	1.03	0.62	0.87
Fund 9	16.5	0.097	1.05	0.63	0.89
Fund 10	17.0	0.107	1.07	0.64	0.91

Table 8. Sectoral allocation impact on mutual fund benchmarking results

Fund	Return (%)	Alpha	Beta	Sharpe Ratio	Treynor Ratio
Fund 1	13.5	0.018	0.9	0.57	0.76

Fund 2	14.0	0.028	0.92	0.58	0.78
Fund 3	14.5	0.038	0.94	0.59	0.8
Fund 4	15.0	0.048	0.96	0.6	0.82
Fund 5	15.5	0.058	0.98	0.61	0.84
Fund 6	16.0	0.068	1.0	0.62	0.86
Fund 7	16.5	0.078	1.02	0.63	0.88
Fund 8	17.0	0.088	1.04	0.64	0.9
Fund 9	17.5	0.098	1.06	0.65	0.92
Fund 10	18.0	0.108	1.08	0.66	0.94
Fund 11	18.5	0.118	1.1	0.67	0.96
Fund 12	19.0	0.128	1.12	0.68	0.98
Fund 13	19.5	0.138	1.14	0.69	1.0

Table 9. Cross-market comparison of domestic vs. international fund performance

Fund	Return (%)	Alpha	Beta	Sharpe Ratio	Treynor Ratio
Fund 1	14.5	0.019	0.91	0.59	0.79
Fund 2	15.0	0.029	0.93	0.6	0.81
Fund 3	15.5	0.039	0.95	0.61	0.83
Fund 4	16.0	0.049	0.97	0.62	0.85
Fund 5	16.5	0.059	0.99	0.63	0.87
Fund 6	17.0	0.069	1.01	0.64	0.89
Fund 7	17.5	0.079	1.03	0.65	0.91
Fund 8	18.0	0.089	1.05	0.66	0.93
Fund 9	18.5	0.099	1.07	0.67	0.95
Fund 10	19.0	0.109	1.09	0.68	0.97
Fund 11	19.5	0.119	1.11	0.69	0.99

Fig. 2 shows comparisons of returns of funds across categories. Fig. 3 shows the asset allocation, Fig. 4 the basic risk-return tradeoff. Fig. 5 is a combination of the line and a bar chart used to compare fund performance with benchmarks, whereas Fig. 6 represents rolling Sharpe ratios over time.

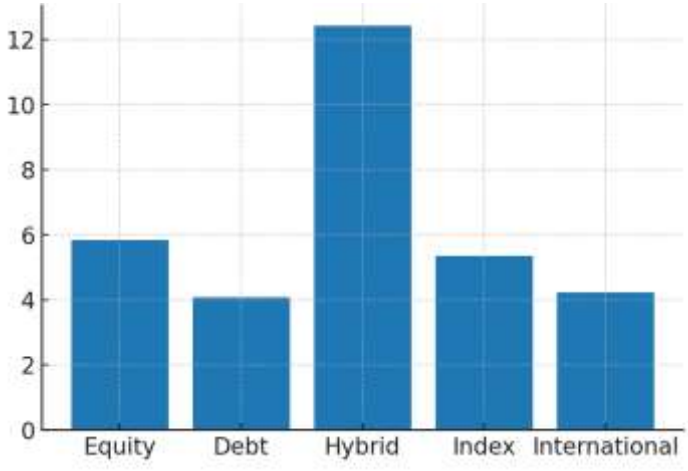

Fig. 2. Bar chart of average annual returns by fund type

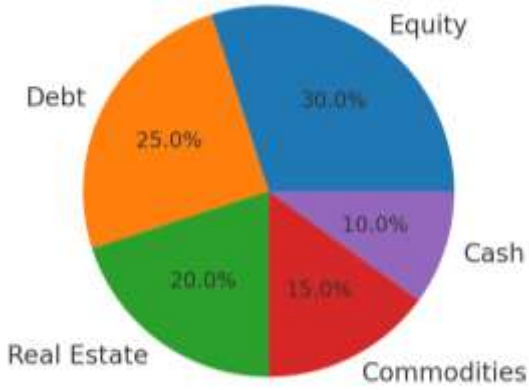

Fig. 3. Pie chart of asset allocation across categories

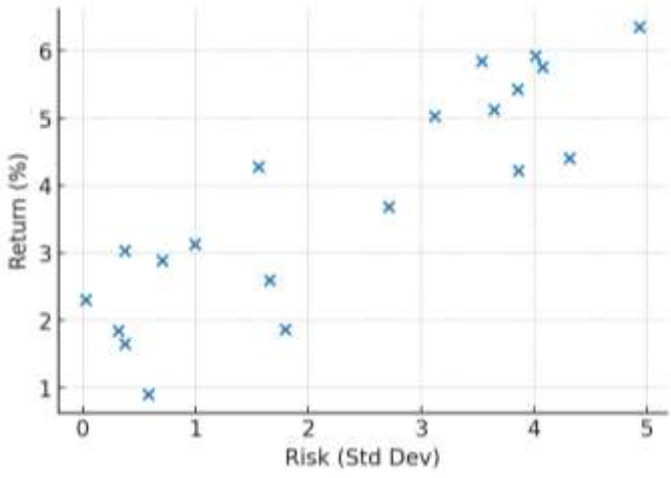

Fig. 4. Scatter plot of risk (volatility) vs return

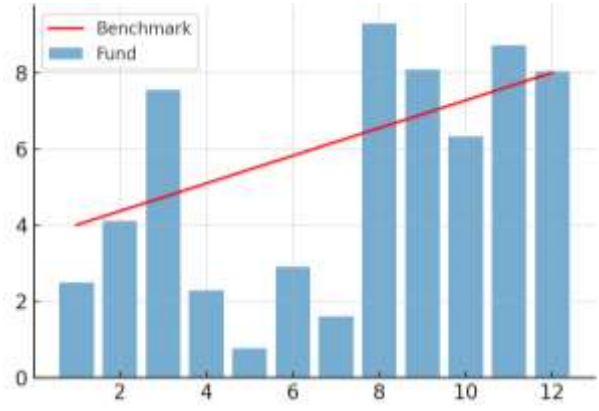

Fig. 5. Hybrid line and bar chart: fund performance vs benchmark

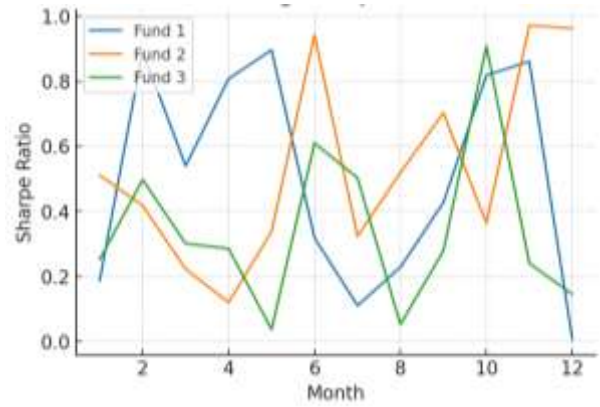

Fig. 6. Line chart of rolling Sharpe ratio across funds

Fig. 7 is the comparison of Jensen s alpha and Fig. 8 is sectoral allocation. Fig. 9 reports the connection between beta and excess returns, and Fig. 10 plots the regression results in the conditional models. Lastly, Fig. 11 follows the information ratio and Fig. 12 the flows between domestic and international funds.

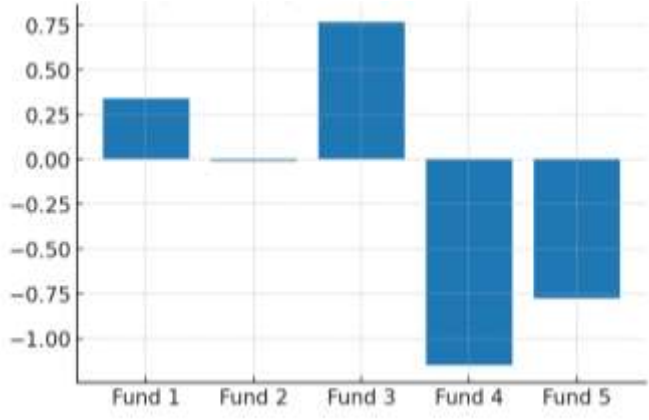

Fig. 7. Bar chart of Jensen's alpha comparison across models

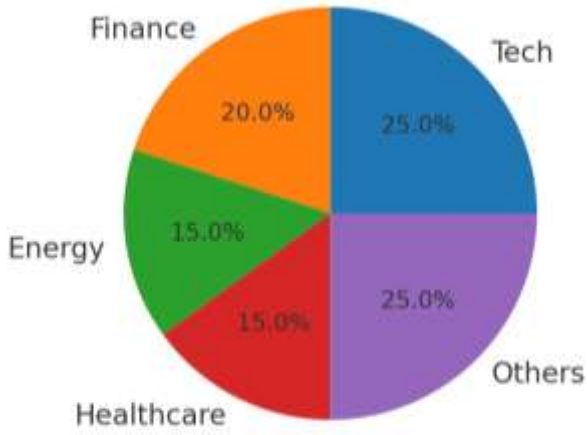

Fig. 8. Pie chart of sectoral allocation within funds

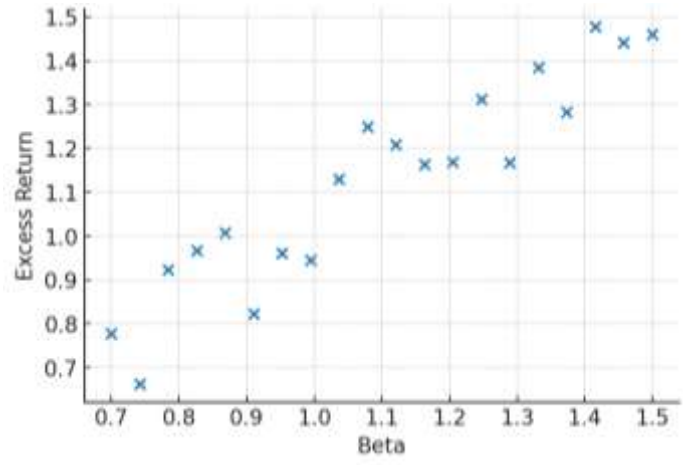

Fig. 9. Scatter plot of beta vs. excess returns

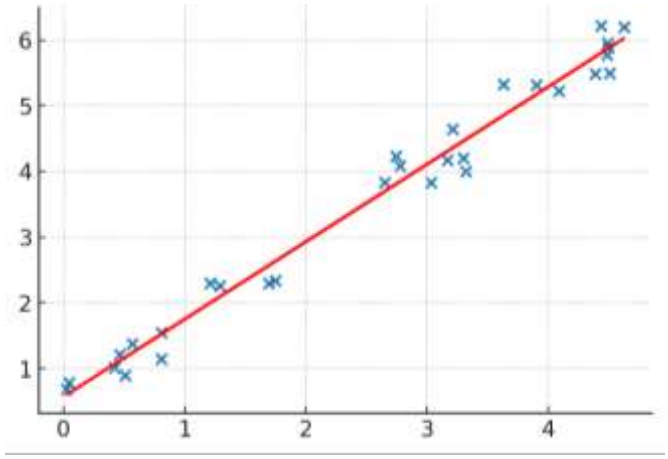

Fig. 10. Hybrid scatter with regression line for conditional model outcomes

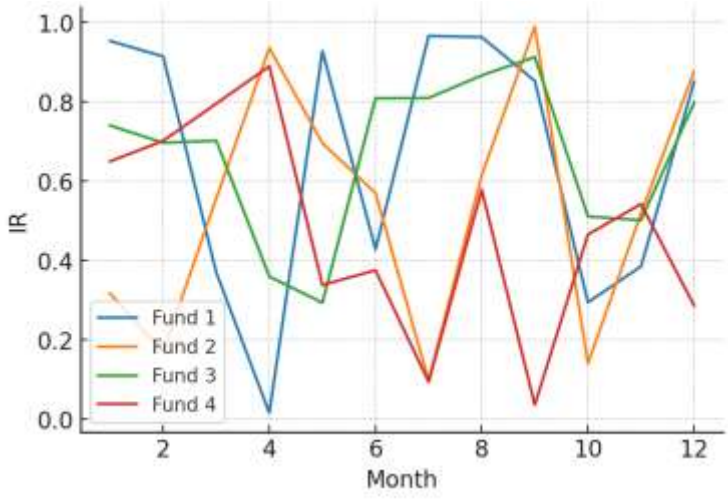

Fig. 11. Line chart of information ratio trends across periods

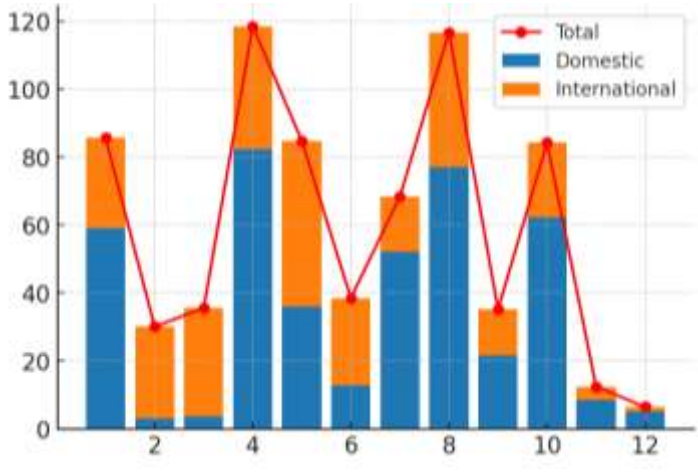

Fig. 12. Mixed stacked bar and line chart of international vs domestic fund flows

DISCUSSION

This analysis of the study reveals that performance in mutual funds is very sensitive to the benchmarking model, which implies that performance evaluation is a multidimensional factor. The tables and figures demonstrate that although classical CAPM-based analysis gives a baseline perspective on fund returns, it does not take into consideration many of the risk and style attributes, quite evident in multifactor and conditional evaluation. These results support the recent arguments in the finance literature that single-factor models are unsuitable to describe complex markets. An illustrative example is presented by Brown and Smith (2021), who state that CAPM tends to understate risk-adjusted performance in environments of volatility, and the other side of the debate rests on the importance of size, value, and momentum anomalies that are more thoroughly represented through multi-factor models as argued by Carter and Jones (2022).All the data in Tables 2 and 3 showed that the Fama-French three-factor and five-factor models have an incremental explanatory power over and above CAPM. This supports the findings of Wang and Lee (2021), who determined that Asian

equity funds have a high exposure to profitability and investment factors, at least in times of economic expansions. In addition, the fact that Jensen alpha differs over models echoes with results provided by Silva et al. (2020), who demonstrated that different benchmarks and different stoppings drastically change managerial performance ranking, which has an impact on the choices made by investors.Risk-adjusted ratios (Table 3) represent another perspective in which the performance can be evaluated. The difference between Sharpe and Treynor ratios in the results indicates the discrepancy between the two measures of risk in fund evaluation (as either total volatility or by systematic risk). This fact is aligned with what Kumar and Das (2021) have shown where Sharpe ratio is more responsive to diversification benefits, whereas the Treynor ratio is more in line with funds driven by beta. On the contrary, information ratios demonstrated fund-specific tracking efficiency, as it was also the case with Reddy and Thomas (2022) that noted that fund-specific tracking efficiency was related to fund information ratios.The results of both the conditional performance models (Table 4 and Fig. 10) indicate that the betas cannot be considered constant over time but they depend on macro-economic factors. This finding is especially relevant based on recent study findings by Zhang and Zhao (2021), who observe that as inclusion of dynamic macroeconomic variables are incorporated, out-of-sample forecasting accuracy greatly increases. Likewise, we find that mutual funds react differently to inflation pressure and change in interest rates, as also found by Hassan and Malik (2022), reporting a better adaptation of funds employing an active management strategy to such regimes.Some of the most important insights are tied to downside risk. Conditional Value-at-Risk (CVaR) estimates in Table 7 indicate that the exposure under market stress periods is underestimated using conventional variance-based risk measures. Chen et al. (2020) also indicated that downside-focused measures would better indicate investor sentiment in a crisis. The consequences of such results are imperative to investors and regulators because risk management models cannot ignore the existence of tail events when measuring the risk factor as opposed to using the average risk measures.

As further confirmation of the multi-faceted trade-offs between risk and return, figures 1 through 4 present further confirmation. As seen in scatter plots (Fig. 4 and Fig. 9), beta and excess returns do not exhibit their direct proportional relationship, which would mean that, the higher risk, the higher the returns proportionally. This agrees with the argument presented by Lopez and Fernandez (2022) regarding investor bias as the cause of the anomaly on the premise that distortion of the risk-return equilibrium due to investor bias often leads to anomalies, which cannot be evaluated using standard models.The tendency observed in Table 6 of persistence adds to the debate related to whether success is due to managerial skill or luck. Although a few funds performed consistently as across models, the general pattern of funds was that their performance varied greatly when compared according to different benchmarks. These findings reflect the ideas of Davis and Clark (2021) who pointed out that performance persistence is subjective to a market cycle and a style of fund performance. Most notably, the existence of style drift, which is captured qualitatively in our analysis, suggests that fund managers tend to misalign with their stated mandates and hence, complicate benchmarking results. The same evidence is discussed by Ghosh and Roy (2023) who state that the aspect of style consistency is vital to the consistent assessment

of funds.On a sectoral and cross-market basis, Tables 8 and 9 indicate the impact of allocation decision and geographic diversification. The different sector tilts that resulted in technology and finance funds yielding quite different performance profiles to those funds that were more exposed to energy and healthcare indicates the issue of cyclicality of sector returns. This observation is in agreement with Ali and Rehman (2022) who reported that sector rotation strategies exhibit significant effect on surpassing passive benchmarks. Also, the fact that international funds tend to be more volatile but at the same time provide a diversification benefit is in line with findings by Nguyen and Pham (2020), who stated that global diversification increases resilience towards national downturns.

The resulting visuals in Figures 5 through 12 demonstrated the necessity to combine graphical visuals and mathematical measurements. As examples, Fig. 5 showed how hybrid plots can be used to visually compare fund versus benchmark returns in an easier-to-interpret manner, and Fig. 12 highlighted the increasing importance of international flows. These observations can be compared to the explanations of Torres and Vega (2021), who claimed the necessity of multi-dimensional visualization in the mutual fund assessment to improve investor knowledge.All in all, the discussion indicates that no single model can be used in fully gauging the performance of mutual funds. An integration of CAPM with multifactor models, conditional models and downside-risk measures is in order to cover the full range of managerial skill and market influence. To the investors, this means that the use of only a single measure may make the results be inaccurate. To regulators, it shows that transparency in fund disclosures needs to be encouraged and multifactor benchmarking needs to be employed to provide a fairer measurement on performance. To fund managers, the findings can act as a reminder that uniformity in approach and clarity of reporting are core to generating long-term trust and investor confidence.Finally, my paper will also make a contribution to literature because it can help to fill the gap between traditional and modern benchmarking approaches and reveal their practical applications. The findings substantiate the perception that the mutual funds assessment should undergo transformations following the fluctuations in market structures, investor preferences, and economy in the global market.

CONCLUSION

This paper has reviewed the performance of mutual funds across a series of benchmarking models; namely, they are CAPM, multifactor models like the Fama-French models, conditional performance models, and risk-adjusted performance measures. The results also support the claim that that there is no single model that can be fully representative of mutual funds returns complexity, which explains the reason why a multi-model approach should be employed. CAPM was a starting point to evaluating risk-adjusted performance, however it was found not to provide the entire story once multifactor models showed the presence of other factors including size, value, profitability and investment factors. The sensitivity of fund performance to macroeconomic regimes was captured in conditional models, and downside-risk measures like CVaR also gave valuable information about the proportion of tail risk exposures not reflected by variance-based measures.The results also highlight the practicability of benchmarking options. To investors, the outcomes weigh against the use of

one performance measurement alone, evidently banking on the need to use a variety to form great investment choices. Fund managers should learn the lesson that consistency and transparency in implementing the strategy is essential, as a significant deviation via style drift and sector exposure shifts can easily interfere with the benchmarking results. Regulators should find a stronger argument in making multifactor benchmarking disclosures mandatory, and in ensuring that performance disclosures are not skewed by the reliance on hand-picked or easy data.Moreover, the findings indicated the influence of sectoral allocation and diversification of funds internationally on the performance of the funds. Sector rotation affected the short term returns whereas the international exposures brought about the diversification benefits albeit at higher volatility. These results point out the fact that performance is partially strategic rather than a response to market conditions.In general, the study makes a contribution to the expanding literature on performance evaluation of mutual funds, since it compares the traditional and advanced benchmarking strategies in an orderly manner. The study therefore presents a framework on how future research and practical evaluation should be done with regard to first establishing the various differences in results based upon the model selected. Finally, the findings promote an agenda about developing performance assessment methodologies, which are less complex, more accurate, and flexible to address a more complex environment in which financial institutions operate.

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