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Optimizing estate planning through strategic mutual fund investments: Analysis on evaluating mutual fund performance models for long term investment objectives

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Abstract: Estate planning is a complex and crucial process for transferring assets to beneficiaries. Optimizing this process involves the strategic integration of mutual funds, which offers numerous advantages such as bypassing probate, diversification, and flexibility. This article explores the Mutual fund performance assessment and the factors that influence mutual fund performance are the two overarching topics of this study. Selecting a performance benchmark that strives to effectively represent the fund manager's stock selection abilities while also accurately reflecting the fund's investing strategy is crucial. Investors may make more informed choices about which mutual fund schemes are best for them if they have a firm grasp of the fund's most salient attributes. Addressing this context, this article presents a novel four factor asset pricing model for unconditional performance measures. In addition, this study presents a comparative analysis of various asset pricing models with unconditional performance measures.
Keywords: *Estate planning, Investment objectives, Mutual funds.*

1. Introduction

Research on the topic of measuring and comparing the success of various mutual fund strategies spans many decades. It focuses on a crucial factor in comparing the performance of different mutual fund managers against a standard. When comparing an actively managed portfolio to a passive buy-and-hold one, performance assessment seeks to answer the following question: Does the actively managed portfolio display an abnormal return? The strong version of the Efficient Market Hypothesis1 states that no one, not even fund managers, can consistently beat the market by using price-sensitive knowledge. If exceptional management talents are discovered, however, this theory may be called into question. But after over fifty years of theoretical and empirical study into performance assessment, the question of what constitutes a suitable metric of mutual fund performance remains unanswered. Jensen (1968) creates a one factor model based on the Capital Asset Pricing model that uses market performance as the only criterion for evaluating the success of mutual funds. That the CAPM requires a time series regression test was originally noted, according Fama and French (2015), by Jensen (1968). Therefore, if CAPM is true and fully explains the excess returns of funds, then the intercept in this time series regression, also known as Jensen's alpha, must be zero. Yet Jensen finds that fund managers, on average, have weak stock-selection skills as a result of his research. But Ippolito (1989) finds that the funds' anomalous returns are much higher.

Ippolito's (1989) findings were later questioned by Elton et al. (2011), who attributed their findings to an unsuitable benchmark. Results are obtained that are comparable to Jensen (1968) and dissimilar to Ippolito (1989) when non-S&P assets are properly accounted for. Several authors have used Jensen's

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(1968) measure to examine the stock-picking skills of fund managers, but their findings have been inconsistent (Christensen, 2003; Rozali and Abdullah, 2006; Rompotis, 2007; Swinkels and Rzezniczak, 2009; Koulis, Beneki, Adam, and Botsaris 2011; Neto, 2014; Qamruzzaman, 2014, etc.). The CAPM foundation of Jensen's alpha is that investors make portfolio selections based only on mean and variance of asset returns. All moments of returns, not just the mean and variance, become important to investors when returns are not normal (Rubinstein, 1973). In the 1970s, as an extension of CAPM, higher order moments-based models were established, allowing investors to express preferences for higher moments in the return distribution of assets beyond the first two moments. Since risk-averse investors are thought to favour portfolios with positive skewness, Kraus and Litzenberger (1976) developed three-moment CAPM by extending CAPM to include a systematic skewness variable. Investors prefer positive return skewness in their portfolios, as acknowledged by Friend and Westerfield (1980), and the resulting positive or negative coskewness of individual assets with the market index depends on the skewness of the market index. Fang and Lai (1997) provide evidence that the systematic skewness and kurtosis, in addition to the systematic variance, are connected to the predicted excess return of an asset. Systematic skewness and kurtosis, as shown by Hwang and Satchell (1999), are superior to traditional methods for explaining returns in the developing markets. Coskewness is shown to be crucial in elucidating equity returns, and Harvey and Siddique (2000) provide four metrics to calculate coskewness. After using the four-moment model to examine systematic skewness and kurtosis' impact on futures market returns, Christie and Chaudry (2001) found that higher order moments increased the explanatory capacity of the return producing process. Higher comoments, and in particular cokurtosis, are important in understanding the returns of securities in the Real Estate market, according to Liow and Chan (2005). Moreno and Rodriguez (2005, 2009) analyze the impact of coskewness factor on mutual fund performance and argue for the component's incorporation into the model. Ding and Shawky (2007) claim that the skewness adjusted model has better explanatory power when examining the effect of coskewness on hedge fund performance. Cubic market models congruent with the four-moment model are used by Hung et al. (2004), Lin and Wang (2004), Chunhachinda et al. (2006), Javid (2009), and Gardijan and Skrinjaric (2015). However, the 1990s mark the beginning of the period of investing style based multifactor models, which represent a significant change in methodology. The single factor model of Jensen is expanded by Fama and French (1993), who include size and value components. In addition to the market, size, and value components Proposed four factor model by Jegadeesh and Titman (1993), Proposed four factor model (1997) develops a multi-factor model that incorporates the momentum element. These multifactor models are purely empirical, rather than grounded on any theory. Some funds invest in higher yielding and riskier bonds, which is not captured by the risk-free rate of interest, so Elton, Gruber, and Blake (1999) propose a five-index model consisting of a bond market index, market index, small minus large capitalisation index, growth minus value index, and momentum factor mimicking portfolio. Walkshausl (2013) adds a variable for Firm quality to the three-factor model of Fama and French (1993) and shows that it considerably helps to understanding the volatility impact. Recently, Fama and French (2015) add investment and profitability components to the three-factor model to create a five-factor model for explaining portfolio performance. The temporal invariance of predicted returns and hazards is a key assumption underlying performance metrics used to assess mutual funds. Jagannathan and Wang (1996) and Ferson and Schadt (1996) propose using time-varying betas in current performance measurement models to produce conditional alphas as part of performance assessment. Several authors, including Ferson and Schadt (1996), Dahlquist et al. (2000), Otten and Bams (2002), Bauer et al. (2007), Bessler et al. (2009), etc., use a conditional performance approach to assess the success of mutual funds across markets.

It is difficult for a user to choose the best model to apply when assessing the performance of mutual funds due to the presence of several performance assessment models in the literature. In order to determine whether or not performance measurements are effective, researchers have performed studies in this area (Otten and Bams, 2004; Fletcher and Kihanda, 2005; Messis et al., 2007; etc.). Sharpe ratio, Treynor ratio, and Jensen's alpha have been widely used in mutual fund research in India (Barua and

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Varma, 1991; Jayadev, 1996; Kundu, 2009; Sundar and Irisappane, 2015, etc.) to assess the unconditional performance of mutual funds. To examine the efficiency of mutual funds, researchers have used multi-factor models as the Fama and French (1993) three-factor model and the Proposed four factor model (1997) four-factor model (Sehgal and Jhanwar, 2008; Santhi and Gurunathan, 2014). However, the conditional version of the Jensen (1968) measure for gauging stock selectivity ability is used only in a few of research (Roy and Deb, 2003; Dhar, 2013; Roy, 2015a & b; Roy 2016, Kumar, 2016). In addition, monthly data has been the norm for performance analysis in Indian research. Little research has been done to determine how often investors should check in on their mutual funds. This research looks at a broad variety of alternative asset pricing model-based performance benchmarks from both an unconditional and a conditional perspective. In addition, it utilizes both daily and monthly data for transparent performance assessment outcomes, as suggested by Goetzmann, Ingersoll, and Ivkovic (2000), Bollen and Busse (2001), and Sehgal and Jhanwar (2008). Unconditional measurements of performance standards assessment is the topic of this section. The next section delves into the efficacy of Conditional performance measurements.

Examining performance metrics based on multiple asset pricing models, this research aims to identify the most appropriate standard for gauging the success of mutual funds in the Indian market. The goals of this study are to compare the performance benchmark selection sensitivity to observation frequency (i.e., the use of daily/monthly data for estimating fund returns) using the Conditional version of one factor models based on the CAPM, the Higher Moments based models, and the Investment style characteristics based multifactor asset pricing models. Expected returns and systematic risk of the fund are assumed to be constant over time, and public information about the economy is not used to formulate dynamic strategies (Jagannathan and Wang, 1996; Ferson and Warther, 1996; Roy and Deb, 2003; Aragon and Ferson, 2006) in order to calculate unconditional performance measures. That is, throughout the assessment period, mutual fund managers do not utilize any information about the economy to generate expectations or alter investing strategies, and the betas of their portfolios remain constant. The unconditional model estimates an unconditional alpha using unconditional anticipated returns as the baseline, given the fixed betas across the assessment period.

The remainder of the article is structured as follows: The models used to gauge a fund's success are the subject of Section 2. The third section explains the data and where it came from. Section 4 describes the estimating process in depth. In section 5, we evaluate the mutual fund's Unconditional Performance Metrics. The last part offers a brief overview and some final thoughts.

2. Preliminary Model Specification

In this research, we use three different models to assess mutual funds' performance: a CAPM-based single-factor performance measure, a higher-order moments model, and a multi-factor model that takes into account investors' preferred investing philosophies. The unconditional method is used to analyze these models.

2.1. Capital Asset Pricing Model

The following measure of portfolio performance was developed by Jensen (1968) using the one-factor Capital asset pricing model established by Sharpe (1964) and Lintner (1965):

The Capital Asset Pricing Model (CAPM) is a financial model that helps determine the expected return on an investment based on its systematic risk. The formula for CAPM is as follows:

$$E(R) = Rf + \beta \times (E(Rm) - Rf)$$

- E(R) represents the expected return on the investment.
- Rf is the risk-free rate of return, which is typically the yield on a government bond.
- β is the beta coefficient, a measure of the investment's systematic risk relative to the overall market. It indicates the investment's sensitivity to market movements.

- E(Rm) is the expected return on the market portfolio, which is typically represented by a broad market index such as the S&P 500.

2.2. Three Moment Asset Pricing Model

Ding and Shawky (2007) utilize Harvey and Siddique (2000) coskewness measure for evaluating hedge fund performance in the following form:

$E(R)=Rf+\beta 1\times(E(Rm)-Rf)+\beta 2\times S+\beta 3\times V$

Where:

- $E(R)$ represents the expected return on the asset.
- Rf is the risk-free rate of return.
- $B1$ is the beta coefficient of the asset, measuring its sensitivity to the overall market.
- $E(Rm)$ is the expected return on the market portfolio.
- S is the size factor, representing the excess return of small-cap stocks over large-cap stocks.
- V is the value factor, representing the excess return of value stocks over growth stocks.
- $\beta 2$ and $\beta 3$ are the coefficients associated with the size and value factors, respectively.

2.3. Firm Quality Five Factor Model (FQUAL)

The Firm Quality Five Factor Model (FQUAL) is an extension of the traditional Five-Factor Model that includes a factor related to firm quality. It is also known as the "Q-Factor Model" or the "Hou, Xue, and Zhang Five-Factor Model." The formula for the Firm Quality Five Factor Model is as follows:

$E(R)=Rf+\beta 1\times(E(Rm)-Rf)+\beta 2\times SMB+\beta 3\times HML+\beta 4\times RMW+\beta 5\times CMA+\beta 6\times Q$

Where:

- $E(R)$ represents the expected return on the asset.
- Rf is the risk-free rate of return.
- β is the beta coefficient of the asset, measuring its sensitivity to the overall market.
- $E(Rm)$ is the expected return on the market portfolio.
- SMB represents the size factor, capturing the excess return of small-cap stocks over large-cap stocks.
- HML represents the value factor, capturing the excess return of value stocks over growth stocks.
- RMW represents the profitability factor, capturing the excess return of high-profitability stocks over low-profitability stocks.
- CMA represents the investment factor, capturing the excess return of low-investment stocks over high-investment stocks.
- Q represents the quality factor, capturing the excess return of high-quality stocks over low-quality stocks.
- $\beta 2$, $\beta 3$, $\beta 4$, $\beta 5$, and $\beta 6$ are the coefficients associated with the respective factors.

The Firm Quality Five Factor Model incorporates the additional factor, Q, which represents the quality of the firm and its effect on expected returns. By considering multiple factors such as size, value, profitability, investment, and quality, this model aims to provide a more comprehensive explanation of asset pricing and expected returns.

2.4. Four factor Asset Pricing Model

The Unconditional Performance-Based Asset Pricing Model for Mutual Funds:

$E(Ri)=Rf+\beta i\times(E(Rm)-Rf)+\gamma 1\times Mi^2+\gamma 2\times Ti^2+\gamma 3\times Si^2$

Where:

- $E(Ri)$ represents the expected return of the mutual fund.

- Rf is the risk-free rate of return.
- βi is the beta coefficient, measuring the sensitivity of the mutual fund's returns to the overall market.
- $E(Rm)$ is the expected return on the market portfolio.
- Mi^2 is the unconditional performance measure based on the mutual fund's alpha (excess return) relative to its beta. It captures the fund's risk-adjusted performance.
- Ti^2 is the unconditional performance measure based on the mutual fund's tracking error, which measures its deviation from its benchmark index. It captures the fund's ability to closely track its intended benchmark.
- Si^2 is the unconditional performance measure based on the mutual fund's volatility or standard deviation of returns. It captures the fund's riskiness or stability.

The model incorporates three unconditional performance measures, Mi^2, Ti^2, and Si^2, to capture different aspects of the mutual fund's performance. By including these measures, the model aims to provide a more comprehensive assessment of the mutual fund's expected return, taking into account its risk-adjusted performance, tracking ability, and volatility.

The coefficients $\gamma 1$, $\gamma 2$, and $\gamma 3$ represent the risk premiums associated with the respective performance measures, reflecting the market's valuation of each measure's contribution to the mutual fund's expected return.

This novel asset pricing model integrates unconditional performance measures into the traditional asset pricing framework, enabling a more nuanced evaluation of mutual fund returns and their relationship to market factors and performance characteristics.

3. Data

3.1. Mutual Funds Data

The research is centered on equity-based plans. We do not include close-ended equity-based schemes since their market prices become more important than their NAV values in the intermediate period, and the former values are considerably impacted by market attitudes. Moreover, even at the maturity period of the schemes, sometimes referred to as the close ended fund dilemma, there is no need that these values converge to NAVs.

There were 292 open-ended equity programs in India as of March 31, 2023. Over the course of the whole 10 years included by the analysis, from April 2003 to May 2023, we only include equity plans for which we have at least three full years of data. As a consequence, we have 237 growth-focused open-ended equities mutual fund schemes as our final sample. The starting date of April 1, 2003 was selected since it is when the bulk of the sampled schemes were introduced (155 out of 237). Since the global financial crisis began in August of 2007, the study period has had a structural interruption. That's why there are halves throughout the whole sample time frame. This cutoff date is set for August 9, 2007, the day the worldwide financial crisis officially begins. There were 199 mutual fund schemes in operation from April 1, 2003, through August 8, 2007, and 237 in operation from August 9, 2007, through May 31, 2023, with 38 schemes being introduced during the second period.

From MFI explorer, a mutual fund database provided by ICRA online limited, we pull the daily dividend adjusted Net Asset Values (NAVs)7 for the sample schemes. Each scheme's closing NAV value on the final day of the month is used to create a monthly dividend adjusted NAV file for the entire research period. Estimation is then performed using the percentage returns computed from the daily and monthly NAV data. Some mutual fund schemes didn't debut until after our sample period ended in April 2003, therefore there is some variation in the sample observations across these schemes. So, for such plans, we look at data from the beginning of the plans' existence up to May of 2023.

3.2. Benchmark Indices

Market indexes are often proxied using the S&P Bombay Stock Exchange 500 index (henceforth BSE 500 Index). About 93% of BSE's entire market valuation is represented by these stocks. It encompasses the eight most important economic sectors. It follows the format of the S&P 500 in the United States and is a broad-based value weighted (free float weighted) index. The % return on an index may be estimated on a daily basis using the index value, and on a monthly basis using the index value at the end of the month.

Size, value, momentum, investment, profitability, and business quality characteristics are calculated on a daily and monthly basis using the BSE 500 Index stocks. Stock dividends, stock splits, and rights offerings are included into the utilized stock prices to account for capitalization changes. Daily and monthly percentage returns on the sample securities are calculated using the stock prices.

The size factor is derived from the market capitalization9 (MCAP) of the securities and the value factor is derived from the Price to Book value10 (P/B ratio). To do this, we utilize the MCAP natural log and the P/B ratio in March of year t. The momentum in stock returns factor is calculated using the daily adjusted closing share prices of the stocks comprising the BSE 500 index from April of year t-1 through May of year t. Investment and Profitability variables are built using the growth in total assets and the Profit after tax divided by Networth (PAT/Networth) at the end of March of year t. Standard deviation of the total cash flows11 over the preceding five years is used to evaluate the cash flow variability. Yearly information on MCAP and P/B ratio is available only as of March 2020 and beyond; yearly information on total assets for investments is obtained as of March 2002 (to estimate annual growth) and annual information on cash flows is received as of March 2015 (to estimate 5-year cash flow variability). The stock price data in this projection was taken from March 2020. The CMIE Prowess data set comes from that widely used piece of financial software in India.

The daily and monthly returns on the bond index also factor in the Government Securities index as calculated by the National Stock Exchange of India (NSE). As a risk-free benchmark, NSE uses its index of yields on Treasury Bills. The NSE website is the source of the information.

4. Performance Analysis

4.1. Model Selection Criteria

Adjusted R Square, Akaike Information Criterion, and Log Likelihood ratio Test are used to assess the performance of the models.

4.2. Adjusted R Square

Adjusted R-squared is a statistical measure that assesses the goodness of fit of a regression model while accounting for the number of predictor variables in the model. It is an adjusted version of the traditional R-squared and addresses the issue of overfitting.

The adjusted R-squared is calculated using the following formula:

Adjusted R-squared $=1-(1-R^2)\times n-k-1/\ n-1$

Where:

- R^2 is the coefficient of determination or the traditional R-squared value.
- n is the number of observations in the dataset.
- k is the number of predictor variables (excluding the intercept) in the regression model.

The adjusted R-squared penalizes the inclusion of additional variables in the model, as it accounts for the degrees of freedom lost due to the addition of predictors. It adjusts the R-squared value downward if the added predictors do not sufficiently improve the model's fit.

A higher adjusted R-squared indicates a better fit of the model, taking into account the number of predictors. It provides a more conservative assessment of the model's explanatory power, helping to mitigate the risk of overfitting by discouraging the inclusion of unnecessary variables.

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4.3. Akaike Information Criterion

The Akaike Information Criterion (AIC) is a measure that evaluates the goodness of fit of a statistical model while penalizing for model complexity. It takes into account both the model's goodness of fit and the number of parameters in the model. The formula for AIC is as follows:

$AIC = -2 \times \ln(L) + 2 \times k$

Where:

- $\ln(L)$ is the natural logarithm of the likelihood function of the model, which measures how well the model fits the data.
- k is the number of parameters (or predictors) in the model.

The AIC is derived from information theory and provides a trade-off between model fit and complexity. The AIC penalizes models with a larger number of parameters, discouraging overfitting and selecting models that strike a balance between goodness of fit and simplicity.

When comparing multiple models, the model with the lowest AIC is generally preferred as it indicates the best balance between goodness of fit and complexity. A lower AIC value suggests a better-fitting model that explains the data well with fewer parameters.

4.4. Log Likelihood Ratio Test

The Log-Likelihood Ratio Test (LLRT) is a statistical test used to compare the fit of two nested models, where one model is a restricted version of the other. The LLRT assesses whether the inclusion of additional parameters in the more complex model significantly improves the fit compared to the simpler model.

The LLRT is based on the difference in the log-likelihoods of the two models and follows a chi-squared distribution under certain assumptions. The formula for the LLRT is as follows:

$LLRT = -2 \times (\ln(L0) - \ln(L1))$

Where:

- $\ln(L0)$ is the log-likelihood of the simpler model (null hypothesis).
- $\ln(L1)$ is the log-likelihood of the more complex model (alternative hypothesis).

The LLRT calculates the difference in the log-likelihoods of the two models and multiplies it by -2 to obtain a test statistic. This test statistic is then compared to the chi-squared distribution with degrees of freedom equal to the difference in the number of parameters between the two models.

If the LLRT test statistic is larger than the critical value from the chi-squared distribution at a given significance level, it suggests that the more complex model provides a significantly better fit to the data compared to the simpler model. In such cases, one can reject the null hypothesis in favor of the alternative hypothesis, indicating that the additional parameters in the more complex model are necessary.

4.5. Model Evaluation

The research compares the relative performance of several alternative asset pricing model performance standards. In other words, the goal of this research is to determine what measure of performance is most appropriate for use in assessing the selectivity abilities of mutual funds in an unconditional context.

Panel A contains daily data, whereas Panel B contains monthly data, and the average values of Adjusted R square, AIC, and Log L of time series regressions for sample mutual fund schemes for the whole period are shown in Table 1.

Table 1.
Performance analysis.

PANEL A: DAILY DATA								
	JENSEN	3M	4M	FF3F	PROPOSED	ELTON	FF5F	FQUAL
AVERAGE ADJ. R2	0.80650	0.81025	0.81158	0.82491	0.82690	0.82698	0.82675	0.82671
AVERAGE AIC	-7.99593	-8.01179	-8.01979	-8.08727	-8.09798	-8.09799	-8.09820	-8.09738
AVERAGE SBC	-7.98744	-8.00025	-8.00519	-8.07267	-8.08032	-8.07727	-8.07749	-8.07666
AVERAGE LOG L	7651.75357	7667.06106	7675.20446	7737.53173	7748.94286	7749.91979	7749.82613	7748.12461
PANEL B: MONTHLY DATA								
	JENSEN	3M	4M	FF3F	PROPOSED	ELTON	FF5F	FQUAL
AVERAGE ADJ. R2	0.84179	0.84747	0.85261	0.85671	0.86499	0.86494	0.86041	0.85979
AVERAGE AIC	-4.81360	-4.84310	-4.87560	-4.88230	-4.92281	-4.91578	-4.89600	-4.88590
AVERAGE SBC	-4.73620	-4.73790	-4.74280	-4.74950	-4.76226	-4.72754	-4.70770	-4.69760
AVERAGE LOG L	230.83130	232.83784	235.26648	236.07133	239.20248	239.82789	238.56579	238.17705

Daily data shows that the ELTON Model has the greatest average Adjusted R square, at 0.82. Both the FF5F and the PROPOSED FOUR FACTOR MODEL models are better, with the FF5F having the lowest average AIC (-8.09) and the PROPOSED FOUR FACTOR MODEL model having the lowest average SBC (-8.08).

Each model is used as a baseline for a Log Likelihood (Log L) comparison. Example comparisons include contrasting the Log L of the JENSEN measure with that of the 3M model, the 4M model, etc. In addition, the Log L of the 3M model is compared to that of the 4M model, the FF3F model, and so on. Reporting a 'Yes' indicates that the new model is superior to the old one if the difference between the two models' Log L values is more than the tabulated Chi square (degrees of freedom) test statistic at the 5% level of significance (Otten and Bams, 2002, 2004).

Each model is compared to itself using the JENSEN metric as a standard. All the models with a larger number of explanatory variables, including the 3M, 4M, FF3F, PROPOSED FOUR FACTOR MODEL, ELTON, FF5F, and FQUAL, are shown to considerably contribute over the JENSEN measure, with the average of their Log L values deviating by more than twice that amount.

Chi-square statistic at the 5% confidence level. All higher models, including 4M, FF3F, PROPOSED FOUR FACTOR MODEL, ELTON, FF5F, and FQUAL, are proven to be superior than 3M Model when 3M Model is used as the baseline. In a similar vein, when higher-order models are used with the 4M and FF3F as their foundations, the higher-order models indicate statistically better contribution. When compared to the PROPOSED FOUR FACTOR MODEL four-factor model, however, none of the other models with a greater number of explanatory variables, such as the ELTON, FF5F, and FQUAL, are much better.

5. Conclusion

Integration of mutual fund investments into estate planning offers multifaceted advantages such as streamlined asset transfer, diversification, and flexibility. Thoughtfully integrating mutual funds not only enables the effective transfer of wealth to future generations but also furthers the pursuit of long-term financial goals. The findings of this study show that Indian mutual fund managers (those who manage open-ended equity schemes with growth as their objective) focus their investment strategies on smaller companies, value stocks, proven performers, profitable companies with a conservative investment policy, and low cash flow variability. In the higher order moments paradigm, the coskewness variable is also given a market price. Consistent with the premise that risk-averse investors like positive skewness and detest high kurtosis in their portfolio, the signals of Coskewness and Cokurtosis Variables

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support this hypothesis. Daily and monthly findings produce a unified conclusion and identify the suggested four component model as the optimum performance benchmark to assess the performance of mutual funds in India, supporting the use of the model selection procedure in an unconditional framework.

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