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Posted Date: 12 November 2024

doi: 10.20944/preprints202411.0647.v1

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Research Paper

Performance Evaluation of Portfolio Management Services and Alternative Investment Fund Schemes: An Indian Perspective

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Abstract: Purpose: The Indian financial landscape has undergone substantial transformation over the past few years, with the increasing popularity of portfolio management service (PMS) companies and alternative investment funds (AIFs). Hence, this study aimed to comprehensively evaluate the performance of different PMSs and AIFs in India. Design/methodology/approach: Our sample consisted of the top 30 PMS funds and 15 AIFs, for which data were available for at least three years. Findings: PMS funds outperformed the benchmarks by an average of 61 bps per month, with more than two-thirds showing statistically higher returns. However, PMS funds did take additional risk to generate higher returns, as they had a significantly higher variance than their respective benchmarks but compensated with higher Sharpe ratios. Using the Treynor–Mazuy and Henriksson–Merton methods, our analysis showed that PMS Fund managers are skilled at stock selection and market timing. Meanwhile, in terms of average returns, AIFs beat the benchmarks by 52 bps; however, the returns among individual funds were not consistent, with some funds reporting more than double the returns of others. Our analysis revealed that AIFs generated significantly higher returns than their benchmarks. Nonetheless, the riskiness of their portfolios was not significantly lower than that of the benchmarks. Originality: This study is the first to compare the returns of PMSs and AIFs with benchmarks to check whether they can outperform their respective benchmarks and provide better risk-adjusted returns.

Keywords: Alternative investment fund; Portfolio management service; Investment performance; Risk-return ratio

1. Introduction

India's financial landscape has undergone a notable transformation in recent years. This change has been fueled by an expanding investor base looking for investment opportunities outside traditional asset classes. This demand for diversification and potentially higher returns has fueled the rise of two key investment vehicles: alternative investment funds (AIFs) and portfolio management services (PMSs). PMSs are a type of investment service that offers customized and personalized portfolio management to high-net-worth individuals (HNIs) or institutional investors. PMS providers usually levy fees determined by either the total value of the assets being managed or the portfolio efficiency. On the one hand, PMSs can offer investors various benefits, such as access to professional expertise, diversification, risk management, tax efficiency, and flexibility. Additionally, PMSs offer a high degree of customization, tailoring investment solutions to individual client needs and risk profiles. On the other hand, AIFs pool funds from multiple investors and invest in a spectrum of assets, including real estate, hedge funds, and private equity. Both PMSs and AIFs cater to a sophisticated and growing segment of investors seeking to achieve their financial goals through strategic portfolio management.

The PMS and AIF wealth under management had a robust compound annual growth rate (CAGR) of 16%. According to forecasts by PMS Bazaar, the total funds under management will exceed INR 28 lakh crores by 2028, compared with the current assets under the management of

mutual funds of INR 59 lakh crores. While it took more than 60 years for the mutual fund industry, PMSs and AIFs took less than 10 years to achieve explosive growth. This does not include funds brought in by venture capitalists and private equity funds (PEs), which fall under a separate category of AIFs. Despite the explosive growth in funding, research on this topic is scarce. Our study is the first to compare the returns of PMSs and AIFs with benchmarks to check whether they have managed to beat their respective benchmarks and provide better risk-adjusted returns. We also examine the returns of these two investment vehicles to check for substantial variances in risk and returns between them. Our motivation is to determine whether the reason for such a strong appetite for PMSs and AIFs is the exceptional track records of these funds.

Investors are directly responsible for the taxes on capital gains and dividends from PMS investments. This can be a complex process, and investors may need to consult tax advisors. The taxation of AIF investments can vary depending on the AIF category and the underlying assets. Some AIFs offer tax benefits, while others may be taxed at the fund level, thereby simplifying tax filing for investors.

This study contributes to existing literature in several ways. To the best of our knowledge, this study is the first to comprehensively analyze the performance of different PMSs and AIFs in India. After analyzing the performance of the top 30 PMS funds in India, as classified by the PMS and AFI database provider as of March 31, 2024, we affirm that at least 70% of these mutual funds are capable of generating statistically superior returns compared with their respective benchmarks. Furthermore, approximately 30% of PMS funds were able to generate higher returns despite having a lower risk, as measured by the standard deviation, compared with their respective benchmarks. On average, the top PMS funds generate 62 bps of excess returns per month. Using the various metrics to analyze the risk-reward relationship (e.g., the Sharpe, Treynor, and information ratios), we can conclude that PMS funds generate returns commensurate with risk. Additionally, using the Treynor–Mazuy and Henriksson–Merton methods, our analysis shows that PMS Fund managers are skilled at stock selection and market timing. We analyzed 15 AIFs that had data for more than four years, and on average, these funds generated 52 bps over their respective benchmarks. However, the number of funds generating higher returns without additional risks was insignificant.

The remainder of this paper is structured as follows. The next section reviews the related literature, defines the research gap, and presents the research hypotheses. Then, we describe the data and methodology used in the analysis. Subsequently, we present and discuss the results. Finally, we summarize the main conclusions.

2. Literature review and hypotheses development

Numerous studies have evaluated mutual funds with no concrete evidence that the top-performing funds beat benchmarks on a consistent basis. Further, the ability of fund managers to time the market or choose stocks is not well supported by the data. Moreover, limited research has examined the risk-adjusted returns of PMS funds in the Indian context, with most studies focusing on individual PMS funds. Aggarwal and Vadgama (2022) investigated the fee structure of PMSs and returns over longer time horizons. Their study of 17 PMS funds showed that HNWI should invest in PMSs with a ten-year horizon as in the longer term, as these funds are able to justify their fees. Naveenan (2019) arrived at a similar conclusion based on an analysis of PMSs by Reliance Nippon, finding that the returns of all PMS schemes managed by the fund were negative for up to six months, but an investment period of three years and beyond provided better returns. Regarding AIFs, although several studies have examined the regulatory aspect and flow into these funds, none have examined the performance of individual AIFs. In 2021, Dey reviewed the significant modifications implemented by the Securities Exchange Board of India (SEBI), which eliminated restrictions on investment by granting permission to simultaneously invest in AIFs and directly in the securities of investee companies.

Table 1. Comparison of mutual funds (MFs), portfolio management services (PMSs), and Alternate Investment Funds (AIFs).

Particulars	MFs	PMSs	AIFs
Definition	A financial vehicle comprising a pool of money collected from investors to invest in stocks, bonds, money markets, and other assets.	A service offered by a portfolio manager with investment in stocks, fixed income, debts, cash, and other individual securities. It can be tailored to meet specific investment objectives.	A privately pooled investment vehicle that collects funds from sophisticated investors, whether Indian or foreign, to invest it in accordance with a defined investment policy for the benefit of its investors.
Investor Category	Retail and high net-worth individuals (HNIs)	HNIs	HNIs and Ultra HNIs (UHNIs)
Minimum Investment amount	INR 500	INR 50 lakhs	INR 1 Crore
Approach	Investor money is pooled.	A separate demat account, that is, a separate portfolio, for every client is maintained.	Investor money is pooled.
Performance	MFs have to take care of diversification rules, valuation guidelines, and redemption-related regulations. Therefore, they are benchmark hugging and, thus, their returns are similar to the benchmark.	PMSs are not regulated in terms of stock/sector concentration limits as in the case of MFs; thus, they are riskier than MFs. However, their returns are much greater for the same reason.	AIFs give investors an avenue to pool funds with the flexibility to invest in derivatives, listed and unlisted equity shares, debt instruments, real estate, hedge funds, and so on. Thus, they are riskier than PMSs, and their returns are greater than those of PMSs and MFs.
Fees structure	There is only an expense ratio that is adjusted in the NAV of the fund.	Management fees, and either a fixed fee/performance fee or a combination of both.	Management fees and either a fixed fee/performance fee or a combination of both, with a huddle and a watermark rate. However, their fee structure is more complex than that of PMSs.
Types	MFs are divided into five broad categories and 36 subcategories, as follows: Solution-Oriented Schemes (2) Hybrid Schemes (7) Equity Schemes (10) Equity Schemes (10) Debt Schemes (15) Other Schemes (2)	Discretionary PMSs: The portfolio manager is entrusted with the responsibility of managing the clients' funds, which includes selecting stocks and making investment decisions. Non-discretionary PMS: (A consultative investment approach involving the portfolio manager's recommendation of investment ideas)	Category I: Venture capital, Infrastructure, and Angel and social venture funds. Category II: Private equity funds (PE funds), funds for distressed assets, and real estate funds. Category III: Investment by private and hedge funds in publicly traded equity funds.

Singh et al. (2019) concluded that AIFs provide the most effective near- and medium-term strategies for increasing renewable energy access to capital markets in India while simultaneously addressing the underlying structural issues. Panda and Deb (2024) conducted a cross-country analysis of AIFs in 28 countries. They discovered that value-at-risk (VAR) models were insufficient for accurately measuring potential negative outcomes. Their research emphasized the importance of caution among investors and fund managers who rely solely on popular VaR models to manage downside risk in AIFs. They also suggested the need for additional research to develop more efficient risk management strategies for AIFs, especially considering their complex structure and asymmetric return distributions. Minutha and Jagannathan (2022) analyzed the notable disparity in AIF dedication that occurred in India during the periods before and after the Covid-19 pandemic,

specifically from 2018 to 2021, and determined that the AIF industry exhibited substantial disparities before and after the onset of the Covid-19 pandemic. Specifically, there was a notable increase in AIF commitment before and after the Covid-19 pandemic. In other words, the amount of funds raised in 2020 exceeded that raised in the previous year. Their study found a robust positive correlation between the performance of the Bombay Stock Exchange Index, which consists of 500 stocks, and investors' financial commitment to AIFs. Since there has been no research on the measurement of AIF and PMS performance in India, we examined research from other countries and the methods used in other studies.

One of the main questions that investors face when choosing a PMS is whether it can outperform other investment alternatives, such as mutual funds, index funds, or self-managed portfolios. Several studies have attempted to answer this question by comparing the returns, risk, Sharpe ratio, Treynor ratio, and information ratio of PMSs with those of other investment options. Nevertheless, the results are mixed and depend on the sample period, methodology, benchmarks, and market conditions.

Chen et al. (2019) conducted a comparative analysis of the performance of PMSs and mutual funds in China from 2007 to 2016 and found that PMS funds have higher average returns, lower risks, and higher Sharpe ratios than mutual funds. They attributed this superior performance to the higher flexibility, customization, and specialization of PMSs. They also found that PMS performs better in bear markets than in bull markets, suggesting that they have better downside protection.

Bhattacharya and Daouk (2014) compared the performance of PMSs with that of self-managed portfolios in the US from 1999 to 2009 and found that PMS portfolios have lower returns, higher risks, and lower Sharpe ratios than self-managed portfolios. They explain this inferior performance by the agency problems, information asymmetry, and moral hazards that arise between PMS providers and investors. They also find that PMSs have higher turnover, higher fees, and lower tax efficiency than self-managed portfolios, implying that they incur higher transaction costs and tax liabilities.

Several studies have analyzed the characteristics of PMS using different data sources, methods, and measures. The results show that PMSs vary widely in their characteristics and are influenced by various factors, such as market conditions, investor preferences, and the regulatory environment. Kale et al. (2013) analyzed the asset allocation of PMSs in the US from 2000 to 2010 and found that PMSs allocate more to equities, less to bonds, and more to alternative assets than average investors. They also find that PMSs have a higher exposure to small-cap, value, and momentum stocks than market portfolios. They argued that a PMS seeks to exploit market inefficiencies and anomalies by investing in these asset classes. They also found that PMSs adjust their asset allocation in response to market conditions, investor preferences, and regulatory changes.

A key issue in PMS research is the determinants of PMS performance, such as managers' skills, experience, reputation, and incentives. These factors can affect the PMS providers' abilities and motivations to generate superior returns for investors. Hence, several studies investigated the determinants of PMS performance using different proxies, models, and tests. The results suggest that PMS performance is driven by both managers' skills and incentives; however, these effects are moderated by market conditions, investor behavior, and the regulatory environment. Barber et al. (2016) investigated the skills of PMS providers in the US from 1999 to 2011.

Choi et al. (2017) examined the experiences of PMS providers in Korea from 2005 to 2014. The duration of a manager's tenure in managing a PMS was employed as a proxy to gauge the manager's level of expertise. They demonstrated that PMS providers' experience is positively related to performance, assets under management (AUM), and PMS survival, indicating that experienced managers can generate higher returns, attract more investors, and sustain their businesses for longer periods. Further, they pointed out that PMS providers' experience is more important in bear markets than in bull markets, implying that experienced managers can cope better with market downturns.

Another aspect relates to the diversification benefits of investment in AIFs. Gupta (2016) investigated the diversification benefits of incorporating hedge funds into traditional portfolios of bonds and stocks. Using Markowitz's mean-variance and mean conditional VaR (CVaR) portfolio models, they analyzed an investment opportunity set consisting of Indian bonds, stocks, and hedge

funds. Their findings suggest that the inclusion of hedge funds can significantly affect a portfolio's risk-return profile. Although hedge funds may improve diversification benefits in terms of mean-variance optimization, their contribution to overall portfolio risk, as measured by CVaR, may be less pronounced, and the presence of hedge funds introduces autocorrelation challenges in portfolio construction. This finding indicates that the historical relationship between hedge fund returns and traditional asset classes is not a reliable indicator of future performance. They pointed out that hedge fund index returns exhibit a low or negative correlation with bond index returns but a relatively high and positive correlation with equity index returns. This finding supports the notion that hedge funds provide diversification benefits by offering returns that are less correlated with traditional asset classes. In addition, Lo (2001), Geman and Kharoubi (2003), Agarwal and Naik (2004), Malkiel and Saha (2005), Brown and Spitzer (2006), Morton et al. (2006), Giamouridis and Vrontos (2007) reported that hedge fund returns are not normally distributed in most cases. Rather, they exhibit an asymmetric distribution in terms of their higher moments.

Asness et al. (2001) and Getmansky et al. (2004) demonstrated that autocorrelation can significantly affect beta coefficients, variance estimates, and Sharpe ratios. Given the reliance of portfolio selection models on these estimates, it is reasonable to expect autocorrelation to influence portfolio construction. To address this issue, Geltner (1991) Geltner (1993) method removes the effects of autocorrelation from individual data observations, thereby providing more accurate return calculations. Several earlier studies (e.g., Kat and Lu (2002), Loudon et al. (2006), Bianchi et al. (2009)) on hedge funds have successfully employed Geltner's method to mitigate the impact of severe autocorrelation on asset returns.

Another major aspect of evaluating both AIFs and PMS Funds is their ability to pick stocks that can generate a positive alpha for their portfolios and market timing. Several studies deal with market timing ability, and the most widely used methods are the unconditional models of Treynor and Mazuy (1966), Henriksson and Merton (1981). In 1996, Ferson and Schadt (1996) introduced a conditional approach to evaluate fund managers' abilities in terms of market timing and stock picking. Subsequent studies conducted by Ferson and Warther (1996), Christopherson et al. (1999), Gregoriou (2003), and others have confirmed the effectiveness of this method. Consequently, there is widespread agreement that the conditional approach is more precise than the unconditional model in accurately identifying fund managers' true abilities regarding market timing and stock selection.

With respect to AIFs, the literature on AIFs is limited. We have included the literature on hedge funds that are part of Category III AIFs. To evaluate the micro- and macro-level risks of AIFs, Panait and Barangă (2018) proposed an approach to assess the risk of AIFs. This approach involves the creation of a risk management panel consisting of eight risk categories, each with different risk signals. The proposed framework combines several indicators using a time-series cross-sectional approach. However, because AIFs are in their nascent stage, the lack of reports and data limits model testing. Thus, the proposed framework was deliberately made flexible to mechanically deal with the complexity of computing risk ratings. Furthermore, they concluded that self-assessments and market supervisors with essential comparisons among industry players can help asset managers.

Liang (1999) studied hedge fund performance in relation to mutual fund performance. Despite having more volatile returns, this study showed that hedge funds outperform mutual funds in terms of performance and Sharpe ratio because of their superior managerial abilities. The average returns of hedge funds show a positive correlation with fund assets, incentive fees, and the lockup duration.

2.1. Research gap

PMSs as products have been available to investors since the early 90s. However, the SEBI issued guidelines for AIFs only in 2012. Consequently, the only database available for research until a few years ago was PMS Bazaar, which provides only basic details on returns. Access to Indian hedge funds, one of the products of Category III AIFs, was available only on a subscription database called the Eureka Hedge. This database is available only for a few Indian institutions. Consequently, the number of papers published on PMSs and AIFs is limited. Owing to the steep increase in funds for PMSs and AIFs since the outbreak of the COVID-19 pandemic, two new databases have begun

providing data on PMSs and AIFs. The Finalyca platform has full data for more than 200 PMS and 50 AIF schemes. However, data on AIFs are limited, as many AIF schemes have started since the outbreak of the pandemic, and in the absence of regulatory requirements, many schemes do not share their proprietary data. Furthermore, no research on HNWI has been conducted to compare the performance of PMSs with that of AIFs. Hence, this study provides useful insights into which of these two investment vehicles provides a better risk-reward ratio.

2.2. Hypotheses

Our objective is to determine the level of performance of the top 30 PMS funds and Category III AIFs that have data for more than four years using various risk-reward metrics. The hypotheses are as follows:

- H1: The majority of PMS funds have managed to generate returns that beat their respective benchmark.
- H2: PMS funds can outperform their benchmarks in terms of returns without assuming more risk.
- H3: PMS fund managers are skilled at stock selection and market timing.
- H4: The majority of AIFs can generate returns to beat their respective benchmarks.
- H5: AIFs can yield greater returns without assuming more risk.
- H6: AIF managers are skilled at market timing and stock selection.

3. Materials and methods

We extracted the net asset value (NAV) of 30 PMS funds and their corresponding benchmarks from the database over a period of four years. We also extracted NAV data for all AIFs that had data for more than three years. We calculated various risk-reward ratios and assessed AIFs and PMS fund performance by employing the following measures:

3.1. Measures Used for Performance Evaluation

Return Measures: Investments are made to earn rewards. Returns can be defined as the rewards earned from an investment. The monthly returns of the selected MF schemes were calculated with month-end NAVs using the following formula:

$$R_{pt} = \frac{NAV_t - NAV_{t-1}}{NAV_{t-1}} \quad (1)$$

where, R_{pt} = fund returns, NAV_t = NAV current day, NAV_{t-1} = NAV in previous day

Likewise, the bench mark index was computed as:

$$R_{mt} = \frac{Index_t - Index_{t-1}}{Index_{t-1}} \quad (2)$$

where, R_{mt} represents the market return, $Index_t$ and $Index_{t-1}$ present the market index on day t and the previous day.

Risk Measures: Investments are risky. Risk is the potential for variations in investment returns. These risks are neither good nor bad. Investment risk usually refers to the probability that actual returns may be less than expected returns. A direct correlation exists between the risk level of an investment and the amount of returns it generates. As risk increases, so do returns. There are two types of risk: total risk, measured by $SD(\sigma)$, and systematic risk, determined by the beta coefficient (β). The risk involved in the selected mutual fund schemes was determined based on the month-end NAV.

The current study used the following risk measures:

Standard Deviation (σ): This is a measure of return volatility because it compares the actual returns of a mutual fund with its predicted returns. A higher SD indicates a higher investment risk.

Beta (β): Beta (β) volatility in investment returns is quantified by assessing systematic risk and is determined by comparing portfolio returns with market returns.

Risk-Free Rate: It has zero variability in returns. However, this is not associated with risky assets. This is the basis for the performance evaluation of risky investments. In this study, the average monthly yield of 91 days of treasury bills was considered a risk-free rate, particularly because it is guilt-edged and easy to access.

Sharpe Ratio: Sharpe (1966) devised an index to quantify portfolio performance. It is a ratio that measures the relationship between rewards and variability. The average excess return ratio of fund portfolios is calculated as the average of the portfolios' excess returns. Meanwhile, the SD of the returns measures the volatility of the returns over a specific period. Returns are measured relative to the portfolio's total risk and derived from the capital market line (CML). The Sharpe ratio determines fund managers' efficacy in diversifying overall risk and is a beneficial tool for assessing excess return per unit of overall risk. The Sharpe ratio is commonly regarded as an indicator of superior performance, with higher values considered favorable.

Treynor Ratio: Treynor (1965) introduced a performance evaluation metric called the Treynor ratio. This metric is similar to the Sharpe ratio, as it also calculates the additional returns generated by an investment above the risk-free rate, with higher values indicating better performance. The Treynor ratio measures the additional returns generated per unit of systematic risk, specifically beta, in contrast to the Sharpe ratio, which considers total risk. This ratio is also known as the reward-to-volatility ratio.

Information ratio (IR): This metric evaluates the return on investment relative to the level of risk involved. This calculation determines a portfolio's excess returns in relation to its tracking error. Excess returns refer to the portion of the return that is not explained by the benchmark's performance. The information ratio is commonly viewed as an indicator of a manager's proficiency in generating value beyond the benchmark. This ratio also gauges the managers' ability to transform extra risks into extra returns. The Information ratio quantifies the returns above an index and evaluates the consistency of the performance.

$$IR = \frac{R_p - R_m}{SD(R_i - R_m)}$$

R_p =Portfolio return, R_m =Benchmark return,

$SD[R_i - R_m]$ =Tracking error

Treynor-Mazuy Model (TM) (Unconditional): Treynor and Mazuy (1966) enhanced the initial version of the linear market model, which measures excess returns by incorporating a quadratic term as follows:

$$R_p - R_f = \alpha + \beta(R_m - R_f) + r^*(R_m - R_f)^2 + e$$

Where, R_p is the return on the portfolio, R_f is the risk-free rate, R_m is the return on the market, α represents the portfolio's alpha, β is the portfolio's sensitivity to the market, r^* is the coefficient for the quadratic term, which captures the market-timing ability of the portfolio manager, e is the error term.

The authors suggested that by conducting a regression analysis on the disparity between the fund's return and the risk-free return and the disparity between the market's return and the risk-free return, they can calculate a parameter r that represents the market timing ability of the fund manager. If the fund manager lacks the market timing ability, the value of r should not deviate significantly from zero. Their rationale was that if the fund manager focus solely on stock selection and refrains from altering the portfolio beta over time, the plot of the fund's surplus return compared with the market's surplus return would exhibit a linear relationship. If the fund manager attempts to engage in market timing but is unable to accurately forecast the direction of the market, the graph would still exhibit a linear trend, albeit with potentially increased variability. Nevertheless, if the fund manager adeptly times the market by adjusting the portfolio beta in accordance with market

conditions, we can anticipate an above-average beta during periods of market growth and a below-average beta during periods of market decline. In upward-trending markets, the graph depicting the fund's surplus return compared with that of the market is positioned above the linear correlation. Conversely, in downward-trending markets, the graph is positioned below the linear correlation. This creates a curved shape in the graph. The addition of a quadratic term to the linear model effectively captures the curvature.

Table 2. Means and standard deviations of PMS funds and their benchmark

S.No	Fund Name	Average Returns	Benchmark Returns	T-test P-value	Standard Deviation Fund	Standard Deviation Benchmark	F-test P-value
1	Aequitas Investment India Opportunities	2.84	1.45	0	8.58	7.52	0.08
2	Nine Rivers Capital Small Cap Opportunities	2.22	1.45	0	7.61	7.52	0.45
3	Samvitti Capital Active Alpha Multicap	2.95	1.45	0.01	8.92	5.48	0.03
4	Invasset LLP Growth Fund	3.18	1.6	0.02	8.19	5.82	0.01
5	Stallion Asset Core Fund	2.78	1.6	0.02	6.32	3.38	0.03
6	UNIFI Blended Fund-Rangoli	1.89	1.23	0.03	5.94	3.62	0.03
7	AlfAccurate Advisors IOP PMS	1.62	1.26	0.03	5.27	4.86	0.19
8	Ambit Global Private Client Alpha Growth	2.54	1.41	0.03	4.86	3.47	0.05
9	Girik Capital Multicap Growth Equity Strategy	1.89	1.26	0.03	5.41	4.91	0.31
10	ICICI Prudential PMS Contra Strategy	1.82	1.26	0.03	5.24	4.81	0.31
11	ValueQuest Platinum Scheme	1.77	1.14	0.04	5.94	4.81	0.01
12	Green Lantern Capital LLP Growth Fund	2.1	1.32	0.04	6.22	6.2	0.46
13	Accuracap PicoPower	1.98	1.45	0.05	6.49	7.52	0.05
14	Aditya Birla Capital Core Equity Portfolio	1.71	1.26	0.05	5.91	5.25	0.27
15	Buoyant Capital Opportunities Multi-cap	2	1.29	0.05	7.51	4.96	0.03
16	2Point2 Capital Long Term Value Fund	1.75	1.24	0.05	6.41	4.99	0.02
17	Credence Wealth Management Diversified	1.77	1.28	0.05	3.91	3.79	0.43
18	Sameeksha Capital Equity Fund	1.94	1.34	0.05	4.85	4.07	0.26
19	ICICI Prudential PMS Largecap Strategy	1.42	1.13	0.05	4.37	3.82	0.35
20	ICICI Prudential PMS Value Strategy	1.58	1.18	0.05	4.98	4.83	0.38
21	Green Portfolio Special	1.65	1.19	0.05	5.97	5.34	0.31
22	SageOne Investment Core Portfolio	1.76	1.41	0.09	6.5	5.5	0.24
23	ICICI Prudential PMS Growth Leaders	1.44	1.26	0.1	4.71	4.06	0.18
24	Samvitti Capital Long Term Growth	1.76	1.16	0.12	5.93	4.86	0.02
25	Valentis Advisors Multi-Cap	1.83	1.43	0.14	5.74	5.33	0.36
26	SageOne Investment Small Cap Portfolio	2.05	1.4	0.17	6.71	7	0.2
27	360 ONE Phoenix Portfolio	1.88	1.58	0.17	3.78	3.79	0.49
28	Motilal Oswal Value Migration	1.35	1.14	0.17	5.11	4.73	0.29
29	360 ONE Multicap	1.38	1.26	0.19	5.35	4.86	0.36
30	Ambit Investment Advisors Coffee CAN	1.37	1.19	0.32	4.44	4.97	0.16
	Average	1.94	1.33	0.08	5.55	5	0.19

Henriksson-Merton Model (Unconditional): Henriksson and Merton (1981) put forward a comparable and less complex model to assess the market timing skills of fund managers.

This model assumes that market timers are not very sophisticated and that they only have to adjust their portfolio beta depending on the market direction rather than predicting the exact market

movements. To represent this concept, they employed a regression equation that incorporated a dummy variable as follows:

$$R_p - R_f = \alpha + \beta(R_m - R_f) + \gamma[D(R_m - R_f)] + e$$

where D is a dummy variable that takes the value of 0 in rising markets and -1 in falling markets, and β is positive in a bullish or upward market and negative in a bearish or downward market. Consequently, the difference between the two betas is represented by the parameter γ , and a positive and significant value of γ suggests that the fund manager is adept at timing the market. It should be mentioned that the intercept term in both of these models gauges the fund managers' proficiency in stock selection.

4. Results and discussion

We downloaded the NAV data of the top 30 PMS funds and analyzed the data to compute the risk-return metrics. Table II contains information on the average returns, benchmark returns, t-test for comparing means, the standard deviations of funds and benchmarks, and the outcomes of the F-test, which calculated the variance difference.

The top PMS funds generated an additional average of 61 bps per month during the benchmark period. Of the 30 PMF funds, 21 (Or 70%) of the mutual funds were able to beat their benchmarks. More than one-third of the funds had significantly lower standard deviations than their benchmarks.

As a robustness check, we examined the aggregated monthly return data of all PMS funds using the corresponding benchmarks over a five-year period. To identify the significant decline during the COVID-19 pandemic, we performed a t-test; the results are shown in Table III.

Table 3. t-Test: Paired Two Sample for Means.

	PMS Funds	Benchmark
Mean	2	1.56
Variance	39.47	34.85
Observations	1581	1581
Pearson Correlation	0.88	
df	1580	

Table 4. F-Test Two-Sample for Variances.

	PMS Funds	Benchmark
Mean	2	1.56
Variance	39.47	34.85
Observations	1581	1581
df	1580	1580
F	1.13	
P(F ≤ f) one-tail	0.01	
F Critical one-tail	1.09	

It can be definitively stated that at least 70% of the PMS funds outperformed their standards, confirming H1.

Of the 21 funds, nine funds had a significantly higher risk than their benchmark. The results demonstrate that 30% of fund managers could produce superior returns, albeit with increased risk. To conduct a robustness test, we performed an F-test; the results are presented in Table IV.

Considering the significance of these results, we can dismiss the null hypothesis that PMS funds assume greater risk to achieve higher returns. To assess whether PMS fund managers produced

satisfactory returns given the increased level of risk, we computed the Sharpe, Treynor, and Information ratios. The results of this analysis can be found in Table V.

Table 5. Sharpe ratio, beta, Treynor ratio, and information ratio.

S.No	Fund Name	Sharpe Ratio	Beta	Treynor Ratio	Information Ratio
1	SageOne Investment Small Cap Portfolio (SSP)	1.88	0.75	45.96	0.66
2	Samvitti Capital Active Alpha Multicap	1.73	0.9	43.64	1.3
3	Sameeksha Capital Equity Fund	1.72	0.86	24.21	0.98
4	Invaset LLP Growth Fund	1.59	1.06	39.08	0.83
5	360 ONE Phoenix Portfolio	1.57	0.92	18.41	1.85
6	Stallion Asset Core Fund	1.56	0.82	34.61	0.92
7	ICICI Prudential PMS Contra Strategy	1.5	0.97	21.14	0.83
8	Credence Wealth Management Diversified	1.5	0.85	16.89	1.43
9	Valentis Advisors Multi-Cap	1.43	0.95	18.99	0.58
10	Ambit Global Private Client Alpha Growth	1.35	0.93	21.88	0.64
11	Buoyant Capital Opportunities Multi-cap	1.32	1.21	19.29	0.87
12	2Point2 Capital Long Term Value Fund	1.29	0.95	20.59	0.69
13	Aequitas Investment India Opportunities	1.28	0.94	24.02	1.2
14	AccuraCap PicoPower	1.23	0.76	32.72	0.46
15	Green Portfolio Special	1.2	0.91	28.33	0.73
16	UNIFI Blended Fund-Rangoli	1.17	0.96	20.01	0.6
17	Girik Capital Multicap Growth Equity Strategy	1.15	0.9	22.52	0.55
18	AlfAccurate Advisors IOP PMS	1.14	1	12.99	0.32
19	ValueQuest Platinum Scheme	1.12	0.89	31.13	0.47
20	Capitalmind Surge India	1.11	0.92	18.14	-0.15
21	ICICI Prudential PMS Value Strategy	1.09	0.92	16.95	0.3
22	Nine Rivers Capital Small Cap Opportunities	1.09	0.82	12.63	0.62
23	Samvitti Capital Long Term Growth	1.08	1.1	12.94	0.37
24	SageOne Investment Core Portfolio	1.07	0.94	16.64	0.18
25	Aditya Birla Capital Core Equity Portfolio	1.07	1.01	14.77	0.35
26	Ambit Investment Advisors Coffee CAN	1.05	0.76	24.51	0.2
27	ICICI Prudential PMS Largecap Strategy	1.04	0.92	12.44	0.29
28	Green Lantern Capital LLP Growth Fund	1.02	0.79	41.05	0.82
29	Marcellus Consistent Compounders	0.96	0.9	17.17	0.09
30	360 ONE Multicap	0.96	0.95	10.64	0.26
31	Alchemy Capital Management High Growth	0.88	0.97	9.06	-0.16
32	Motilal Oswal AMC Value Migration	0.85	0.96	8.92	-0.09
33	ICICI Prudential PMS Growth Leaders	0.74	0.89	11.83	0.26
	Average	1.23	0.92	21.94	0.58

The majority of funds have a Sharpe ratio higher than one, indicating that investors were rewarded for the risks undertaken. With respect to the Treynor ratio, the figures were skewed by exceptional returns during the last 12 months combined with lower beta values.

The fund managers' ability to capture opportunities is demonstrated by the information ratio, which is, on average, higher than 0.5. Grinold and Kahn (2000) assert that managers in the top quartile possess information ratios of no less than 0.5, with those considered outstanding exceeding an information ratio of 1.0. These figures are deemed universal and should be applied regardless of the asset class, country, or era. Undeniably, a positive information ratio signifies above-average performance, whereas a negative ratio reflects poor performance. Nonetheless, Goodwin (1998) contended that maintaining a high information ratio (over 0.5) can be challenging.

The Trenor–Mazuy and Henriksson–Merton models were used to test PMS fund managers' stock selection and market timing skills. The regression results are presented in Table VI.

The results of the intercept and coefficients of regression (representing alpha, beta, and gamma) are significant. Therefore, we conclude that PMS fund managers have the ability to pick stocks, generate alpha, and time the market, confirming H3.

Regarding AIFs, we extracted the NAV data of 15 AIFs that had data for more than four years and analyzed the data to compute various risk and return ratios. The results are presented in Table VII.

AIFs, on a monthly average before tax, generated an additional 48 bps per month over the benchmarks. We analyzed the consolidated data of all AIF funds and performed a t-test; the results are presented in Table VIII.

The results demonstrate that AIFs outperformed their benchmarks. The only fund with a substantially lower risk than its benchmark was ITI, a long-short fund (as measured by the standard deviation). ITI had lower returns as it took risks, which can be inferred from the funds' beta; therefore, we can attribute the majority of higher returns to the higher risk taken by these funds. We also performed an F-test to check the difference in variance between AIFs and their respective benchmarks; the results are presented in Table IX.

Table 6. Regression results using the Treynor-Mazuy and Henriksson-Merton methods -Test: Paired Two Sample for Means.

Trenor-Mazuy Model				Henricksson-Merton Model			
Regression Statistics				Regression Statistics			
R Square	0.77			Multiple R	0.880305		
Adjusted R Square	0.77			R Square	0.774937		
Observations	1,581			Observations	1,581		
	df	Significance F			df	Significance F	
Regression	2	0		Regression	2	0	
Residual	1,578			Residual	1,578		
Total	1,580			Total	1,580		
	Coefficients	t Stat	(P-value)		Coefficients	t Stat	(P-value)
α	0.638	7.55	0	α	0.762	7.703	0
β^*	0.919	66.99	0	β^*	0.871	41.113	0
γ^*	-0.003	-3.25	0	γ^*	-0.123	-3.823	0

Table 7. Mean returns and standard deviations of ASIFs funds and their benchmark.

Fund Name	Average Returns	Benchmark Returns	t-test P-Value	SD Fund	SD Benchmark	F-test p-value
Aequitas - Equity Scheme I	2.85	1.82	0.01	9.86	7.98	0.06
Whitespace Fund I - Equity Plus	2.22	1.57	0	5.68	5.71	0.49
Altacura - AI Absolute Return Fund	1.19	5.95	0	0.64	8.52	0
ICICI Prudential Growth Leaders Fund	2.01	1.05	0.01	4.44	3.69	0.17
Ampersand Growth Opportunities - 1	3.11	2.39	0.03	4.51	4.48	0.48
Carnelian Capital Compounder Fund - 1	1.99	1.27	0.04	5.91	5.53	0.31
Samvitti Capital Alpha Fund	1.77	0.89	0.05	6.16	5.03	0.06
Guardian Capital Partners Fund	2.84	1.63	0.07	6.35	5.87	0.29
Girik Multicap Growth Equity Fund II	1.58	1.09	0.22	4.58	3.98	0.25
Nippon - The Big Switch	1.28	1.06	0.26	7.16	7.49	0.38
Alchemy - Leaders of Tomorrow	1.54	1.15	0.32	5.92	5.4	0.22
Malabar - Value Fund	1.58	1.37	0.43	7.77	7.62	0.43
360 One - High Conviction Fund	1.72	1.62	0.46	5.73	5.71	0.49

D&B - India Opportunities Multicap Fund	1.38	1.36	0.48	5.4	5.69	0.36
ITI - Long Short Equity Fund	1.35	1.35	0.5	3.44	5.37	0
Average	1.9	1.7		5.57	5.87	

Table 8. t-Test: Paired Two Sample for Means.

	Variable 1	Variable 2
Mean	1.96	1.66
Variance	39.01	36.19
Observations	807	807
Pearson Correlation	0.72	
Hypothesized Mean Difference	0	
df	806	
t Stat	1.87	
P(T<=t) one-tail	0.03	
t Critical one-tail	1.65	
P(T<=t) two-tail	0.06	
t Critical two-tail	1.96	

Table 9. F-Test Two-Sample for Variances.

	Variable 1	Variable 2
Mean	1.96	1.66
Variance	39.01	36.19
Observations	807	807
df	806	806
F	1.08	
P(F<=f) one-tail	0.14	
F Critical one-tail	1.12	

The results reveal that the variance between AIFs and benchmarks is not significant. Therefore, we reject H5.

The Trenor–Mazuy and Henriksson–Merton models were used to test the stock selection and market timing skills of AIF managers. Table X shows the regression results.

Table 10. Regression results using Treynor-Mazuy and Henriksson-Merton methods.

Trenor-Mazuy Model				Henricksson-Merton Model			
Regression Statistics				Regression Statistics			
R Square	0.52			R Square	0.7		
Adjusted R Square	0.52			Adjusted R Square	0.7		
Observations	807			Observations	807		
	df	F	Significance F		df	F	Significance F
Regression	2	433.9	0	Regression	2	922.2	0
Residual	804			Residual	804	11.87	
Total	806			Total	806		
	Coefficients	t Stat	(P-value)		Coefficients	t Stat	(P-value)
α	0.7	4.06	0	α	2.5	16.54	0
β^*	0.74	26.82	0	β^*	0.37	13.96	0
γ^*	0.00	(0.89)	0.37	γ^*	(0.93)	(21.70)	0

The findings demonstrate that AIF Managers can pick stocks with high alpha value; however, we obtained contradictory results in terms of the market timing skill.

Table XI presents our analysis of the Sharpe Ratio, Treynor ratio, and fund information to determine whether fund managers generated returns that matched their risks.

Table 11. Regression results using Treynor-Mazuy and Henriksson-Merton methods

Fund Name	Sharpe Ratio	Beta	Treynor Ratio	Information Ratio
Aequitas - Equity Scheme I	1.45	0.96	30.3	1.16
Whitespace Fund I - Equity Plus	2.04	0.95	27.17	1.99
Altacura - AI Absolute Return Fund	0.76	0.14	28.16	-3.47
ICICI Prudential Growth Leaders Fund	1.76	1.05	20.68	2
Ampersand Growth Opportunities - 1	2.45	0.85	39.6	0.95
Carnelian Capital Compounder Fund - 1	1.56	0.88	24.8	0.55
Samvitti Capital Alpha Fund	1.03	0.89	22.19	0.49
Guardian Capital Partners Fund	1.75	0.96	29.91	0.85
Girik Multicap Growth Equity Fund II	1.1	0.83	12.78	0.53
Nippon - The Big Switch	1.03	0.92	15.51	0.3
Alchemy - Leaders of Tomorrow	1.24	0.16	15.5	0.13
Malabar - Value Fund	0.78	0.8	15.46	0.37
360 One - High Conviction Fund	1.19	0.06	15	-0.17
D&B - India Opportunities Multicap Fund	1.25	0.91	19.78	-0.26
ITI - Long Short Equity Fund	0.81	8.28	0.21	-0.22
Average	1.35	1.24	21.14	0.35

The average Sharpe ratio was skewed by the exceptional performance of the six AIFs with returns greater than risk. Similarly, the AIFs' average information ratios were also skewed by the exceptional performance of the five funds. We note that almost 50% of fund managers had poor ability in terms of capturing opportunities, as their information ratio was less than 0.5 and, in a few cases, negative.

5. Conclusions

This study evaluated the performance of AIF and PMS funds using methods prescribed for mutual funds, hedge funds, etc. The analysis revealed that most PMS funds outperformed their benchmarks. More than 70% of these funds could generate returns higher than their benchmark index, which was reaffirmed by many funds reporting a Sharpe ratio higher than 1. High Information ratio scores indicate fund managers' ability to seize opportunities. Our five-year analysis of mutual fund aggregate data showed that PMS funds outperformed the benchmarks. Our analysis revealed that PMS funds had additional risks for generating higher returns, as they had much higher standard deviations than their benchmarks. However, the returns on these funds compensate for the additional risks. The regression results using the Treynor-Mazuy and Henriksson-Merton methods showed that PMS fund managers can select stocks and time their movements. Meanwhile, the AIFs' performance was less robust, with only 40% of funds outperforming the index, mostly by taking additional risks. However, the aggregate data for all AIFs revealed that the funds generated significantly higher returns than their benchmarks. Further, one-third of the fund managers scored poorly on market opportunity capture.

Author Contributions: Conceptualization, J.K.; methodology, J.K.; formal analysis, J.K.; investigation, J.K.; writing—original draft preparation, J.K.; writing—review and editing, J.K. and S.P.S; All authors have read and agreed to the published version of the manuscript

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Funding: This research received no external funding.

Data Availability Statement: The data used in this research will be available upon request.

Conflicts of Interest: The authors declare no conflicts of interest.

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