Traditional hedge funds vs AI-powered hedge funds

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Abstract

The importance of artificial intelligence (AI) is undeniable to the hedge fund sector. The ability of AI algorithms to analyze data in real time contributes to more informed decision-making and faster response to market changes, leading to higher returns. This enables AI-powered hedge funds to strengthen their market position. Despite the growing role of AI, human evaluation remains a crucial element in the investment decision-making process. This paper compares the performance of traditional hedge funds with that of AI-powered hedge funds under various market conditions. We estimate the performance of the North America hedge funds strategies by using a various measures (sharpe ratio, sortino ratio, tracking error, information ratio, upside capture and downside capture).The analysis covers the period from the beginning of January 2018 to the end of December 2021, divided into two sub-periods: the pre-crisis period and the crisis period, respectively. Our results show that there is no significant difference between the performance of traditional hedge funds and AI-powered hedge funds under various market conditions.

Key words: Traditional hedge funds, AI-powered hedge funds, sharpe ratio, sortino ratio, tracking error, information ratio, upside capture and downside capture ratio, COVID-19 pandemic.

1-Introduction

When people want to invest their money in financial assets, they usually think of investing in traditional investments (stocks, bonds or money market funds), or in traditional investment vehicles such as mutual funds. Beyond such investments, there is another category of investing known as alternative investments. Hedge funds are among the most common and largest these types of investments. Hedge funds, unlike mutual funds, can invest across any asset class (for example, stocks, bonds, currencies, commodities, derivates and others). Hedge funds are also popular due to the high levels of secrecy associated with their activities and the great freedom of their investment operations, which makes them significantly different from the other types of investment funds.

In an increasingly competitive market, hedge funds need every competitive edge they can get. And it's about to be even more competitive for hedge funds that aren't utilizing artificial intelligence (AI).

A handful of hedge funds in North America are using artificially intelligent software to make their investment decisions. The Wall Street Journal reports that some of these funds, such as New York-based Rebellion Research, are using such software to beat the S&P 500 index by as much as 10% a year.

This is where AI comes in. As one of the most debated tech topics on the market, it is quickly being adopted in many industries.

-What is AI?

Over the last several decades, Greater computing power and more data has led to AI use in nearly every sector, including the financial services sector.

The integration of artificial intelligence ("AI") and the financial industry has always been a match made in heaven. High volumes, the quantitative aspect of finance, the need for expediency and accuracy are ideal for the unique skill-set of AI.

The term "artificial intelligence" can be traced back to 1955, but has evolved since then. Today, we define AI as a computer or machine that simulates or initiates human behavior through pattern recognition and advanced algorithms.

AI has numerous applications in various industries. It can create text, analyze data, make analytical predictions, offer insights, and draw conclusions. All of these functions make it perfect for hedge funds.

Advantages, disadvantages of AI:

Advantages of AI	**Disadvantages of AI**
1.**Automation**: AI enables the automation of mundane tasks, freeing up human resources to focus on more creative activities.	**1.Job Displacement:** AI-driven automation has the potential to replace human workers in certain tasks , leading to job displacement and unemployment.
2.Accuracy and Precision: AI systems can process vast amounts of data with high accuracy, minimizing errors and improving the quality of decision-making.	**2.Bias and Discrimination**: AI algorithms can inadvertently perpetuate biases present in training data, leading to discriminatory outcomes in decision-making processes.
3.24/7 Availability: AI-powered systems can operate continuously, resulting availability of services without the need for breaks such as customer support, and online transactions, enhancing convenience for users across different time zones.	**3-Privacy Concerns**: AI technologies often rely on vast amounts of personal data , raising concerns about privacy and data security.
4.Personalization: AI algorithms can analyze user data and behavior to provide personalized recommendations, and services tailored to individual preferences.	**4.Lackof Transparency**: AI models, particularly complex deep learning algorithms, can be opaque , leading to a lack of transparency in decision-making processes.
5.Predictive Analytics: AI enables organizations to leverage predictive analytics, anticipate customer needs, and identify potential risks or opportunities.	**5.Overreliance on Technology**: Overreliance on AI systems without human oversight can lead to overconfidence , particularly in safety-critical domains such as autonomous vehicles and healthcare.
6.Efficient Resource Utilization: AI-driven optimization algorithms can optimize resource allocation, and logistics, leading to cost savings, and improved resource utilization in various sectors.	**6.Ethical Dilemmas**: AI raises complex ethical dilemmas, such as the surveillance technologies, and predictive policing algorithms.
7.Enhanced Healthcare, 8. Improved Safety, 9. Innovative Applications, 10.Global Competitiveness	**7.Social Isolation:** The proliferation of AI-driven technologies, such as virtual assistants and social robots, may contribute to social isolation

AI, ML & DL

For several years, Artificial Intelligence, Machine Learning, and Deep Learning have been used for a huge variety of applications. Although they are related, each of these concepts has its own meaning. Simply put, Deep Learning is a subcategory of Machine Learning, which is itself a subcategory of Artificial Intelligence.

AI-Artificial Intelligence	ML-Machine Learning	DL-Deep Learning
Is the science of enabling machines to act like humans. It aims to give a computer intelligence comparable to that of a human.	Is a field of artificial intelligence focused on developing algorithms that allow computers to learn from data and improve their performance on specific tasks. It enables systems to identify patterns, and make decisions based on the data they are trained on	Is a subcategory of Machine Learning , is a method of automatic learning inspire by the functioning of the nervous system of living beings .

How Hedge Funds Can Utilize AI?

With increasing market competition, hedge funds are seeking to capitalize on every available opportunity, including artificial intelligence (AI) . Many hedge funds utilize AI in functions such as: predicting market corrections, analyzing data, forecasting market trends, predicting supply and demand imbalances, managing risk, detecting fraud, automating research, and executing trades.

When used correctly and with accurate data, AI can enable hedge funds to make informed investment decisions. Whether through investment intelligence or automated trading, AI can help hedge funds optimize their portfolios and better serve their clients. AI can also interpret volatile market trends and improve portfolio performance.

-Investment Intelligence

Hedge fund investors can also use AI-powered technology to help them identify potentially profitable investments. Algorithms will scan all the data they input and make predictions about stock performance.

-Predicting Volatility

With AI, hedge funds can now make more accurate predictions to help them make better trades .Machine learning-based investment algorithms are more efficient at predicting and recognizing patterns, and can increase the accuracy of forecasts.

-Automated Trading

AI algorithms can help automate tedious tasks, and they can also automate trading and time it correctly in the market. Hedge fund managers can set limits for stock options.

Using AI to automate many of these processes reduces human error and improves efficiency, leading to better trades.

-Generating Alpha Factors

Hedge funds use alpha to measure fund performance against a benchmark. This indicates the value a hedge fund manager can add .

When using AI for trading, you can perform feature engineering. Feature engineering can help managers understand all the risks associated with any underlying factors that may affect portfolio returns. Using these new features, higher alpha can be achieved.

-Predicting Market Disruptions

The global COVID-19 pandemic has caused unprecedented stock market volatility that few people anticipated. As AI analyzes more data and begins to detect patterns, it can predict when such global events will occur.

Characteristics of the Hedge Funds Strategies

The term "hedge" comes from the purpose of hedge funds, which is to protect investors' capital during a market downturn. They achieve this by hedging against traditional market risks (equities, interest rates, credit, currency, etc.) to which they are exposed or by investing in alternative asset classes (commodities, real estate, private equity, etc.). A hedge fund is generally highly specialized in a particular area of expertise or strategy.

Hedge funds, or alternative asset managers, offer a wide range of investment solutions. The strategies they employ vary significantly in terms of returns and risk. Some are very weakly correlated with equity markets (such as Relative Value), exhibit very low volatility, and aim to deliver performance regardless of market conditions. When integrated into a traditional stock/bond portfolio, these strategies help reduce overall portfolio volatility thanks to the decorrelation gains they provide. Other strategies, however, are much more volatile than equity markets (such as Global Macro) due to their use of derivatives (options, futures, swaps, etc.), short selling (selling a security that an investor does not yet own with the aim of buying it back later at a lower price and pocketing the difference), or leverage (taking on an investment that exceeds the fund's net assets).

There are many different classifications of the investment approaches applied by the hedge funds. Such classifications are proposed by authors (Lhabitant 2006, Anson2006, Stefanini 2010, ...). Information companies such as Eurekahedge, Hedge Fund Research, BarclayHedge and CreditSuisse also use their own definitions of hedge fund investment. The Eureka Hedge classification is concise, categorizing hedge fund strategies into nine types, as follows:

1-Arbitrage : Managers simultaneously take long positions on undervalued bonds and short positions on overvalued bonds to generate a profit. A manager will apply this technique after identifying price differences between bonds issued by different companies or between securities with the same capital structure.

2- Managed Futures/CTA: This is a systematic strategy that seeks to generate returns by trading global futures and forward markets, often by identifying price trends in various markets.

3- Distressed Debt : focus on firms of that have already declared bankruptcy, or where the market expects the underlying company to go bankrupt, Hedge fund managers typically buy securities these of companies and they then hold the securities until convergence to fair value.

4-Event driven: This strategy focuses on capturing the value gap created when companies undergo transformative corporate events that have yet to be priced by markets but that are expected to have a significant impact on shareholder value. Investments can be made across the capital structure of a company.

5-Fixed income: This strategy exploits anomalies related to movements and distortions in yield curves by taking positions across different maturities of the yield curve. It is implemented through government bonds, futures, options, and interest rate swaps.

These strategies rely heavily on quantitative yield curve models to identify anomalies and track their correction.

6-Long-Short Equity: involves taking long positions (buying "long") whose value is expected to increase, and short positions (borrowing securities to sell them) whose value is expected to decrease (the manager buys them back at a price lower than the amount paid and returns them to the lender).

7-Global Macro: managers seek to profit from the evolution of the world economy driven by changes in government policies that impact interest rates, unemployment and inflation, and subsequently foreign exchange, bond and equity markets.

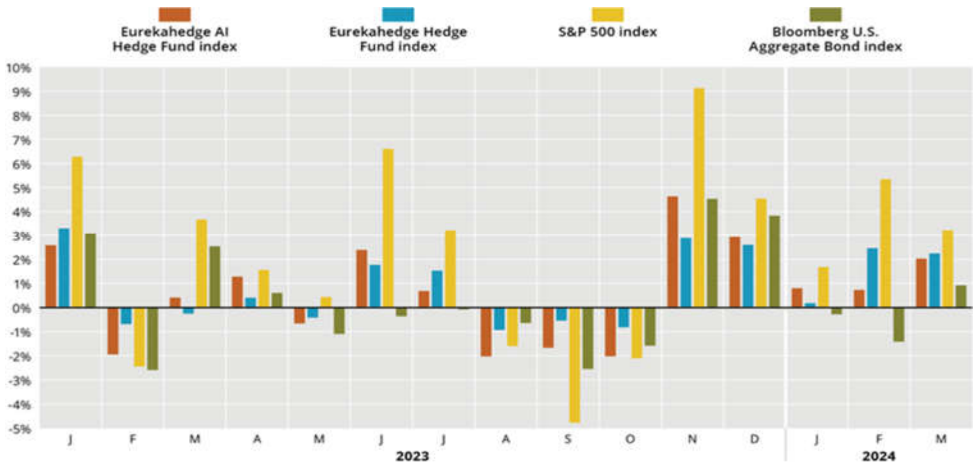
8-Multi-Strategy: Multi-strategy hedge funds are diversified investment vehicles that pool capital to execute various hedge fund strategies within a single fund, allowing managers to dynamically shift capital between them for better risk-adjusted returns, reduced volatility, and consistent performance, independent of overall market direction.

9-Relative Value: Relative value strategies aim to exploit very small price discrepancies that the fund considers unjustified. To do this, hedge funds make extensive use of leverage to amplify the potential for gains (and losses), which involves borrowing cash to increase the effective size of the portfolio (initially composed only of funds contributed by investors).

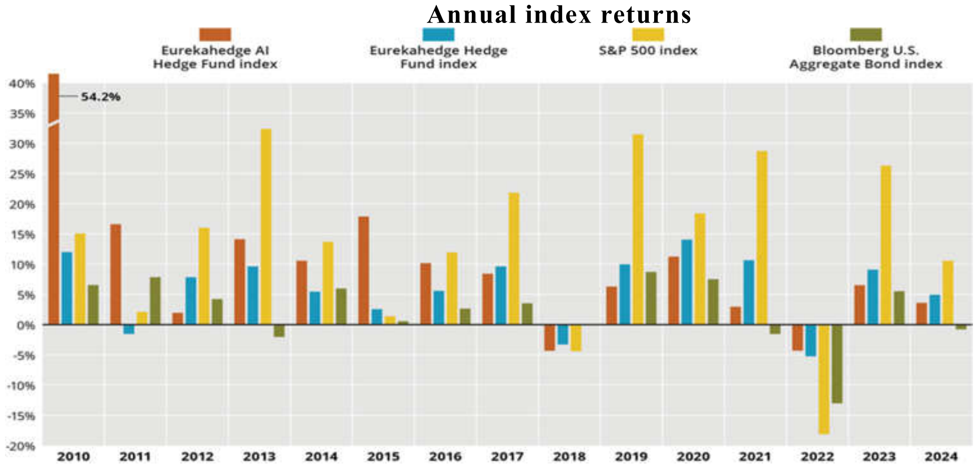
2-Literature review

The integration of Artificial Intelligence has dramatically changed hedge fund management, enabling enhanced decision-making, and risk management. Traditional methods have often relying heavily on historical data and slower processing times. In contrast, AI algorithms empower hedge funds to evaluate vast datasets instantly, and predicting market trends with remarkable accuracy. Many studies examine how Artificial Intelligence influence the performance of hedge funds., highlighting the benefits of predictive analytics, improved risk assessment, and the challenges posed by data privacy and algorithmic bias.

Monthly index return



Annual index returns



Sources: Eurekahedge, Bloomberg

According to these figures, the Eureka AI hedge fund index underperformed the overall Eureka hedge fund index in the short term. In nine of the 15 months ending in March, the AI-powered index averaged a monthly return of 0.7%, compared to 0.9% for the overall hedge fund index. Additionally, the AI-powered index exhibited higher volatility, at 7.1% versus 5.3%. However, in the long term, the AI hedge fund index has generated better long-term risk-adjusted returns. AI-powered hedge funds outperformed overall hedge funds in half of the cases—seven out of the 14 years from 2010 to 2023.[1]

In an effort to better understand how automation affects hedge funds, Grobys.K., Kolari.JW and Niang.J(2022), by using the Preqin Hedge Fund Database, they

1-Larry.R(2024)« Graphic:AI powers hedge funds to strong performance»Pensions&Investments,May 6 manually construct a data set of hedge funds grouped into four clusters: discretionary, systematic, combined, and AIML (automated). Using the CAPM model as well as Fama and French's three-factor and Carhart's four-factor models, they found that hedge funds with the highest level of automation outperform other hedge funds with more reliance on human involvement. Also, they found that a man versus machine zero-cost strategy that is long hedge funds portfolio with highest level of automation and short those with highest level of human involvement yields a highly significant spread of at least 50 basis points per month. They conclude that automation plays an important role in the profitability of the hedge fund industry.

Wenbo Wu & Jiaqi Chen & Zhibin (Ben) Yang & Michael L. Tindall, (2021) apply four machine learning methods to cross-sectional return prediction for hedge fund selection. They equip the forecast model with a set of idiosyncratic features, which are derived from historical returns of a hedge fund and capture a variety of fund-specific information. Evaluating the out-of-sample performance, they find that their forecast method significantly outperforms the four styled Hedge Fund Research indices in almost all situations. Among the four machine learning methods, they find that deep neural network appears to be overall most effective. Investigating the source of methodological advantage of their method using a case study, they find that cross-sectional forecast outperforms forecast based on time series regression in most cases. Advanced modeling capabilities of machine learning further enhances these advantages. they find that the return-based features lead to higher returns than the benchmark of a set of macro- derivative features, and their forecast method yields best performance when the two sets of features are combined.

Tian Ma, Wanwan Wang, Fuwei Jiang (2025) utilize generative AI to predict and classify the performance of hedge funds based on groups of fund characteristics. Compared to commonly used machine learning methods, their method can successfully distinguish high- and low-performing funds across various investment strategies, with the return spread being the highest in the equity hedge strategy at 3.16 % monthly. The results are robust in risk-adjusted return prediction. Trend-based features are the most important predictors of future fund performance. Returns of predictive long-short portfolios are higher following periods of low narrative attention and favorable macroeconomic conditions. The asset allocation exercise highlights the significant economic value of machine learning. their study enriches the burgeoning field of machine learning and artificial intelligence for finance by applying big data techniques to fund selection and allocation.

Tengjia Shu and Ashish Tiwari (2025) advanced that the explanatory power of multi-factor models used to evaluate hedge fund performance is effectively zero for many funds (so-called zero-R2 funds). We find that machine learning algorithms offer significant advantages in tracking fund performance, especially for zero-R2 funds, resulting in more precise estimates of fund alphas and hence more accurate identification of superior funds and fund failures. A key source of the improvement is the ability of machine learning methods to detect changes in the funds' risk exposures with greater accuracy, and the ability to capture the non-linearities and interactions among risk factors that characterize hedge fund strategies.

Emmanouil Platanakis, Dimitrios Stafylas, Charles Sutcliffe and Wenke Zhang (2025) advanced that Prior academic research on hedge funds focuses predominantly on fund strategies in relation to market timing, stock picking and performance persistence, among others. However, the hedge fund industry lacks a universal classification scheme for strategies, leading to potentially biased fund classification and inaccurate expectations of hedge fund performance. These authors use machine learning techniques to address this issue. First, they examine whether the reported fund strategies are consistent with their performance. Second, they examine the potential impact of hedge fund classification on managerial decision-making. The results suggest that for most reported strategies there is no alignment with fund performance. Classification matters in terms of abnormal returns and risk exposures, although the market factor remains consistently the most important exposure for most clusters and strategies. An important policy implication of their study is that the classification of hedge funds affects asset and portfolio allocation decisions, and the construction of the benchmarks against which performance is judged.

3- Methodology and Data

As it was mentioned above, a hedge fund is a private investment fund that pools money from wealthy investors to use complex investment strategies (such as short selling or leverage) to generate high returns, regardless of overall market movements, focusing on absolute rather than relative performance, while remaining less regulated. These characteristics constrain the possibilities to evaluate the portfolio performance of hedge funds using some traditional measures, such as the Jensen model (Jensen, 1967), the Fama model (Fama, 1972) and others. These models assess the portfolio performance using systematic risk, CAPM, and related to them concepts. Therefore, when used to evaluate the performance of hedge funds, they would provide misleading results. In contrast, many authors advanced that the hedge funds performance can easily be evaluated using the Sharpe ratio, tracking error, ,information ratio, and others .

In our analysis we use six tools to measure the performance of hedge funds : Sharpe ratio, sortino ratio ,tracking error, information ratio, upside capture ratio and downside capture ratio.

The Sharpe ratio (Sharpe, 1966) The Sharpe ratio was designed for determining what reward an investor could expect for investing in a risky asset versus a risk-free asset. A higher ratio indicates better performance, as it shows that the investment generates a higher return per unit of risk taken. A Sharpe ratio above 1 is generally considered good, while ratios above 2 or 3 are seen as excellent or exceptional. A negative ratio means that the investment has underperformed a risk-free investment.

$$\text{Sharpe Ratio}= \frac{Rp-Rf}{\sigma p}$$

where: R_p=return of portfolio

R_f=risk-free rate

σ_p=standard deviation of the portfolio

The evaluation of the portfolio of hedge funds , which includes their negative investment results, would give a methodologically correct picture of their investment performance. Some of the measures that meet this requirement are those using downside risk. Most popular among them are the Sortino ratio (Sortino & Price, 1994).

Ratio > 1: The downside risk-adjusted return is excellent. The investment has generated more return than it has taken on in terms of potential loss.Ratio between 0 and 1: The return is acceptable, but there is a moderate risk of loss.Ratio < 0: The investment's return has not reached the minimum expected level, and the investment offers no compensation for the risk taken.High Ratio: A high Sortino ratio is preferable, as it means the investment generates a higher return for each unit of downside risk.Negative Ratio: A negative ratio indicates that the investment is not meeting minimum return expectations and that corrective action is necessary.

Sortino Ratio= $\frac{Rp-rf}{\sigma d}$

where: Rp=Actual or expected portfolio return

r_f=Risk-free rate

σ_d=Standard deviation of the downside

The tracking error measures the performance divergence between a portfolio and its benchmark index. It is calculated as the standard deviation of excess returns (the difference between the portfolio's return and that of the benchmark).Low tracking error (0.1% to 0.5%) Indicates performance very close to the benchmark index, as is the case with index funds or ETFs that closely replicate an index. High tracking error (greater than 1%) Suggests that the portfolio deviates significantly from its index, either positively (higher performance) or negatively (lower performance).

Tracking error=ω= $\sqrt{Var\ (rp - rb)}$

where: Var= the variance

r_p=the return of a portfolio

r_b= the return of a benchmark

The information ratio (Goodwin (1998)) The information ratio measures a fund's performance relative to its benchmark index by assessing the outperformance achieved in relation to the risk taken (tracking error). A high ratio indicates better management, meaning the fund generates consistent outperformance with low risk compared to the index. A high ratio is considered excellent.

Ratio > 1.0 The fund consistently outperformed the index with low risk.0.5 > Ratio < 1.00 The fund outperformed the benchmark index, but less consistently or with slightly higher risk.0.0 > Ratio < 0.5 The fund outperformed the index, but only slightly or with relatively high risk. Ratio < 0.0 The fund underperformed the index or took excessive risk without generating additional returns.

Information ratio= $\frac{\text{Portfolio Return} - \text{Benchmark Return}}{\text{Tracking Error}}$

where: Portfolio Return=Portfolio return for period

Benchmark Return=Return on fund used as benchmark

Tracking Error=Standard deviation of differencebetween portfolio and benchmark returns

There is another set of metrics that can be successfully used to evaluate the performance of hedge funds.These are very simplified ratios, but can provide important information that many of the metrics cannot provide. Morningstar (MorningStar, 2021) defines two of these tools as upside capture indicator and downside capture indicator.

The upside capture ratio measures a fund's performance relative to its benchmark index during periods of rising market conditions. A ratio greater than 1 (or 100%) indicates that the fund outperformed the index, while a ratio less than 1 (or 100%) suggests that it underperformed. A ratio of 1 (or 100%) means that the fund tracked the index's performance during those periods.

Upside capture ratio = (Fund's Returns in Up Months / Benchmark's Returns in Up Months) x 100.

The downside capture ratio measures a fund's performance in bear markets, that is, when the benchmark index is declining. A ratio below 100% is desirable, as it indicates that the fund has lost less than the index, suggesting better risk management. A ratio above 100% means that the fund has underperformed the index during market declines.

Downside capture ratio= (Investment's Return During Down Market / Benchmark's Return During Down Market) x 100

The analysis covers the period from the beginning of January 2018 to the end of December 2021, divided into two sub-periods: the pre-crisis period and the crisis period, respectively. The first sub-period extends from 1 January 2018, to 31 December 2019.The second sub-period runs from 1 January 2020, to 31 December 2021. The primary objective of this division is to compare the performance of traditional hedge funds with that of AI-powered hedge funds, both before and during the COVID-19 crisis in order to highlight its effects.

This study uses monthly North American hedge funds index .According to the Eurekahedge database we extract into nine strategies North America Arbitrage hedge fund(NAAHF), North America CTA/Managed Futures hedge fund(NACTA/HF), North America Distressed Debt hedge fund(NADDHF), North America Event Driven hedge fund(NAEDHF), North America Fixed Income hedge fund(NAFIHF), North America Long /Short Equities hedge fund(NAL/SHF), North America Macro hedge fund(NAMHF), North America Multi-Strategy hedge fund(NAMSHF), North

America Relative Value hedge fund (NARVHF).besides we use the North America hedge fund index (NAHF) and the AI hedge funds index.

The risk-free yield used in the study is the yield of us one-month treasury bill rate (USTB) and the benchmark is the Morgan Stanley Composite Index for the North America region (MSCINA).

4- Empirical Results

Sharpe ratio, Sortino ratio of the hedge fund strategies before and during the COVID-19 crisis Table1

Strategy	Pre-Covid-19 crisis period		Covid-19 crisis period	
	Sharpe ratio	Sortino ratio	Sharpe ratio	Sortino ratio
NAAHF	1.3553	1.4393	0.3564	0.3321
NACTA/HF	2.4881	2.8903	0.5372	0.8541
NADDHF	1.1757	1.4668	0.3746	0.2336
NAEDHF	0.9487	1.3751	0.2300	0.1785
NAFIHF	2.4767	2.9724	0.1641	0.0695
NAL/SHF	0.6601	0.8362	0.3426	0.3879
NAMHF	0.7300	0.8491	0.3871	0.6163
NAMSHF	1.0552	1.5202	0.32715	0.2891
NARVHF	0.7647	0.8305	0.2644	0.2646
NAHF	0.9924	1.3413	0.3572	0.3574
AI HF	1.3605	2.1995	0.2232	0.3632

Table 1 shows the performance of different strategies and AI hedge funds using the Sharpe ratio and the Sortino ratio as performance measures. The sharpe ratio prior to the crisis was highest for the arbitrage, CTA/managed futures, distressed debt, fixed income, multi-strategy and AI hedge funds index. The value of the sharpe ratio of these strategies and AI hedge funds is above 1 (better performance), it shows that the investment generates a higher return per unit of risk taken. The Sharpe ratio of AI hedge funds (1.3605) is higher than that of the North America hedge fund index (NAHF) (0.9924) and most strategies (arbitrage, distressed, event driven, long/short, Macro, multistrategy and relative value) means AI hedge funds is more efficient. It generates a better excess return for each unit of risk (volatility) assumed, compared to the North America hedge fund index (traditional hedge funds). However, the CTA and fixed income strategy has a higher Sharpe ratio than AI hedge funds; even for the Sortino ratio. The situation during the COVID-19 was quite different. The values of the Sharpe ratio of all hedge fund strategies and AI hedge funds are lower than 1. AI hedge funds can find patterns faster, but it can also lose them faster when markets change. Models trained on the last bull run might struggle in a downturn.

The value of the sharpe ratio of all strategies and AI hedge funds during both periods was positive, means that the investment has performed better than a risk-free investment. The value of the Sortino ratio in the pre-crisis period was higher in general. This is due the lower downside risk taken by hedge funds industry. In contrast, during the COVID-19 period the Sortino ration was lower. The downside risk taken by the hedge fund industry during the crisis period is higher compared to the pre-crisis period.

Tracking error, Information ratio of the hedge fund strategies before and during the COVID-19 crisis Table2

Strategy	Pre-Covid-19 crisis period		Covid-19 crisis period	
	Tracking error	Information ratio	Tracking error	Information ratio
NAAHF	-0.0353	-0. 1619	-0.0477	-0.2288
NACTA/HF	-0.0371	-0.1840	-0.0541	-0.2045
NADDHF	-0.0369	-0.1147	-0.0431	0.0119
NAEDHF	-0.0263	-0.2467	-0.0299	-0.1902
NAFIHF	-0.0370	-0.1196	-0.0439	-0.2792
NAL/SHF	-0.0202	-0.2202	-0.0251	-0.1260
NAMHF	-0.0183	-0.5268	-0.0263	-0.0782
NAMSHF	-0.0281	-0.1997	-0.0361	-0.2153
NARVHF	-0.0264	-0.2290	-0.0405	-0.2180
NAHF	-0.0263	-0.1958	-0.0327	-0.1872
AI HF	-0.0339	-0.2240	-0.0464	-0.2653

table 2 shows that all strategies and AI hedge funds have a negative value of tracking error and information ratio (exception NADDHF in covid-19) means that the benchmark outperformed all these strategies and AI hedge funds in both analysed sub-periods.

Upside capture, Downside capture of the hedge fund strategies before and during the COVID-19 crisis Table3

Strategy	Pre-Covid19 crisis period		Covid19 crisis period	
	Upside capture	Downside capture	Upside capture	Downside capture
NAAHF	0.2703	0.2385	0.2469	0.0616
NACTA/HF	0.1389	0.1088	0.2304	0.0349
NADDHF	0.2241	0.0490	0.6582	0.2019
NAEDHF	0.3689	0.4620	0.6138	0.5244
NAFIHF	0.2178	0.0533	0.2788	0.2235
NAL/SHF	0.5088	0.5340	0.6690	0.4765
NAMHF	0.4168	0.7836	0.7243	0.5245
NAMSHF	0.3387	0.3433	0.4363	0.2708
NARVHF	0.4012	0.4812	0.4210	0.3072
NAHF	0.3761	0.3707	0.5156	0.3352
AI HF	0.1724	0.2224	0.2783	0.2261

Table 3 shows that throughout the Covid-19 crisis period, no hedge fund strategy managed to achieve a higher return than the benchmark when it was up. Moreover, no hedge fund strategy achieved a return that exceeds 72.43% of the positive return of the MSCINA Index and only the Distressed Debt, the Event Driven, the Long/short equity , the Macro , and North America hedge fund index (NAHF) achieved returns exceeding 51.56% of its return..During the market downturn , the Event Driven and the Macro strategy had the highest average negative returns. The arbitrage and CTA/Managed Futures are the best performers. The situation is even worse considering the pre-crisis data. During this period, the industry failed to keep pace with the benchmark when it was growing. On the other hand, only the Distressed Debt and Fixed Income strategy are the best performers. As a whole, the values of the up capture indicator are worse than those during the crisis period. During Pre-Covid19 crisis period, when the benchmark grows, AI-based hedge funds underperformed all other strategies (except the CTA strategy). During the market downturn, AI hedge funds outperformed most other strategies. During Covid19 crisis period, when the benchmark grows the Performance of AI hedge funds is better than before the pandemic, but still lower than other strategies (except the arbitrage strategy). During the market downturn, the performance of AI hedge funds is same as before the pandemic but outperformed most other strategies (except the arbitrage, CTA and Distressed Debt strategy).

Conclusion

This study compares the performance of traditional hedge funds with that of AI-powered hedge funds under various market conditions. We estimate the performance of the North America hedge funds strategies by using a various measure (Sharpe ratio, Sortino ratio, tracking error, information ratio, upside capture and downside capture). Our results show that prior to the crisis The Sharpe ratio of AI hedge funds is higher than that of the North America hedge fund index (NAHF) and most strategies (arbitrage, distressed, event driven, long/short, Macro, multistrategy and relative value) means AI hedge funds is more efficient. The tracking error and information ratio presented similar results between AI hedge funds and traditional hedge funds ((NAHF) and others strategies). The upside and downside capture show that AI hedge funds outperformed traditional hedge funds ((NAHF) and most strategies) during the market downturn (in Covid 19and pre-Covid 19 period).

In general, and through an analysis of the various results of these metrics, there is no significant difference between the performance of traditional hedge funds and AI-powered hedge funds under various market conditions. In further research, we will study the performance of individual hedge funds (traditional and AI-powered hedge funds).

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