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The Impact of Artificial Intelligence on Hedge Fund Alpha Generation

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ABSTRACT:
This bachelor's thesis examines the impact of artificial intelligence on hedge fund alpha generation. The purpose is to examine alpha in hedge funds and see how it's evolved recently. Furthermore, the purpose is to look at changes in sources of alpha, and whether there can be seen effects of the use of artificial intelligence on excess returns, for example, in persistence. An important discussion in the literature is whether alpha measures the skill of the manager or is it just a technological edge.

Hedge funds manage trillions of dollars and thus can be seen as a major economic force. Artificial intelligence has been used in the hedge fund industry for years, but recent developments have made it a topic of interest. Generative artificial intelligence has advanced significantly over the past few years. The use of generative artificial intelligence has become increasingly prevalent.

The literature presents differing opinions. At the same time, there is mixed evidence regarding the effects of artificial intelligence on alpha generation in the long term. The literature agrees on technology being a central component in alpha creation. The findings show that artificial intelligence is used to create returns in the vast majority of hedge funds. Some studies raise the possibility that artificial intelligence might make strategies crowded.

KEYWORDS: Hedge Fund, Alpha, Artificial Intelligence, Efficient Market Hypothesis, Adaptive Market Hypothesis, CAPM

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ABSTRACT:

Tämä kandidaatin tutkielma tutkii tekoälyn vaikutuksia rahastojen alphaan. Tarkoitus on tutkia alphaa rahastoissa ja sen muutoksia lähihistoriassa. Lisäksi tarkoituksena on tutkia mahdollista muutosta alphan lähteissä sekä voidaanko nähdä tulossa vaikutusta tekoälyn käytöstä. Esimerk iksi onko sillä vaikutusta alphan pysyvyyteen. Keskeinen näkökulma kirjallisuudessa on se, että heijastaako alpha ihmisen osaamista vain onko se seurausta teknologiasta.

Rahastot hallinnoivat miljardeja dollareita ja siten rahastot voidaan nähdä isona tekijänä maail mantaloudessa. Tekoälyä on käytetty rahastojen hallinnassa jo vuosia, mutta viimeaikaiset kehi tykset tekoälyssä tekevät aiheesta kiinnostavan. Generatiivinen tekoäly on kehittynyt merkittävästi viime vuosien aikana. Generatiivisen tekoälyn käyttö on yleistynyt huomattavasti.

Kirjallisuus aiheesta esittää eriäviä mielipiteitä. Samaan aikaan, tutkimustulokset ovat ristiriidassa tekoälyn vaikutuksista, mutta kirjallisuus on samaa mieltä siitä, että teknologia on keskeinen komponentti alphan tuottamisessa. Tutkimustulokset osoittavat, että tekoälyä käytetään suurimmassa osassa rahastoista. Osa kirjallisuudesta esittää ajatuksen siitä, että tekoäly voi ruuhkauttaa strategioita ja siten heikentää alphaa.

KEYWORDS: Hedge Fund, Alpha, Artificial Intelligence, Efficient Market Hypothesis, Adaptive Market Hypothesis, CAPM

Contents

1 Introduction 5

1.1 Purpose of the study 6

1.2 Structure of the study 7

2 Theoretical Framework 8

2.1 Efficient Market Hypothesis 8

2.2 Adaptive Market Hypothesis 10

2.2.1 Behavioral Finance 11

2.3 EMH vs. AMH 12

2.4 Modern Portfolio Theory 13

2.4.1 Alpha Formula (CAPM-based) 14

3 Literature Review 16

3.1 Hedge Fund Returns 18

3.2 Shift in sources of alpha 22

3.3 Does AI Create or Erode Alpha? 25

3.4 Is Alpha a Measure of Skill or Technology? 29

4 Conclusion 34

References 37

1 Introduction

The hedge fund industry has been growing massively in the past decades. “In 1990, hedge funds managed approximately $39 billion in assets … -current estimates put hedge-fund assets at $2.5 trillion” (Getmansky, Lee & Lo, 2015, p.1). However, more recent data tells that this no longer reflects the present state and hedge fund assets are closer to $3.87 trillion (Grobys, Kolari and Niang, 2022, p. 4632). There are no up-to-date statistics available, but it is probable that the same increase has persisted. As observed, the hedge fund industry has grown exponentially despite the internal turmoil of the finance industry. Managing trillions of dollars globally makes hedge funds a major force in the economic world. Being a major force, they have a great influence on the financial world in its entirety.

Artificial intelligence, known as AI, has become a crucial tool in the economic world, and it has found its way to the hedge fund industry. Hedge funds have started implementing artificial intelligence in their operations. Hedge funds have been acting as pioneers of the financial industry since the 1940s (Wulf, 2019, p. 1). While artificial intelligence is a relatively new concept for many individuals, the industry has been using it for a decade. Wulf speculates that the use of emerging technology could potentially change the financial sector (2019, p. 21). This phenomenon is particularly significant because the use of AI has become widespread. 56% of hedge funds use artificial intelligence or machine learning in their processes (as cited in Wulf, 2019, p.1).

Artificial intelligence in this context means “software used to perform tasks or produce output previously thought to require human intelligence, esp. by using machine learning, commonly known as ML, to extrapolate from large collections of data” (Oxford English Dictionary, 2023). In this context, artificial intelligence is used as an umbrella term. Artificial intelligence also includes machine learning as it is an important part of AI. “Machine learning is the study of computer algorithms that allow computer programs to automatically improve through experience” (Mitchell, as cited in Israel, Kelly and Moskowitz, 2020, p. 2).

Artificial intelligence can be used in hedge fund management, for example to improve decision making, handle risk and enhance trading strategies. Hedge funds gain leverage by using artificial intelligence to automate trading and process broad data sets. Artificial intelligence has evolved considerably in the past decade which has led to technology suitable for companies to process data and help with decision making (Sheng, Sun, Yang & Zhang, 2025, p. 1). Artificial intelligence has been used broadly and in different ways and parts of the processes for a while now. The growing interest comes from advances in recent years and the vast possibilities of future leverage.

This thesis examines the impacts of using artificial intelligence for hedge fund alpha generation. Hedge fund returns can be seen as consisting of two parts: alpha and beta. In the study by Getmansky et al. (2015) alpha is defined as managers generating unique excess expected returns. Alpha is what makes hedge funds different from conventional investment vehicles. Commonly, it's described that alpha comes from informational advantages, exploitation of market anomalies, advanced risk management approaches and overall management skill. Literature has even questioned the structure of the returns and there is disagreement about whether there even is true alpha.

1.1 Purpose of the study

The objective of this thesis is to review the effects of the usage of artificial intelligence on hedge fund alpha generation. Especially the correlation between the two. Whether artificial intelligence can be seen as a positive factor in alpha generation or does it cause the alpha to erode. There are arguments for both sides. This thesis will only examine the implications of artificial intelligence and not go into the technical side of artificial intelligence tools.

Hypothesis 1: The use of artificial intelligence shifts or erodes alpha.

Hypothesis 2: Artificial intelligence is a new source for alpha.

The first hypothesis (H1) suggests that the use of artificial intelligence merely shifts alpha. It would mean that the use of AI is reshaping the alpha. Hedge funds distinctiveness is connected to hedge funds higher performance (as cited in Getmansky et al., 2015, p. 21). Alpha will diminish when it gets crowded. Artificial intelligence could make hedge funds similar thus lessening each one's distinctiveness. That would make the alpha shift and create the need to discover sources.

The second hypothesis (H2) supports the idea that the utilization of AI creates new opportunities for alpha. Alpha is presumed to come from the unique skills of a hedge fund manager (Getmansky et al., 2015). If alpha is a measure of skill, can artificial intelligence assist hedge fund managers? Artificial intelligence has made huge improvements in recent years which could create something new that traditional hedge fund managers haven't yet seen.

1.2 Structure of the study

The purpose of this thesis and the hypotheses are disclosed in the first chapter. The second chapter provides an overview of theories relevant to the topic. The third chapter reviews the literature on the topic and analyses the phenomena. The fourth chapter consists of conclusions.

2 Theoretical Framework

To understand hedge funds and hedge fund returns more deeply, it is important to consider a theoretical framework. The literature presents few theories that are closely related to the hedge fund return creation process. Firstly, there is the Efficient Market Hypothesis and the Adaptive Market Hypothesis. They are relevant to the topic since they offer a view on how AI can simultaneously affect the efficiency of the market and lessen alpha and also at the same time create new opportunities for returns. Behavioral Finance also plays a substantial role. Behavioral finance concepts help to understand the situations that create market anomalies and mispricings. Lastly, there is the Modern Portfolio Theory. The Modern Portfolio Theory is relevant since it provides the Capital Asset Pricing Model, which is the starting point of assessing alpha and differentiating it from beta.

2.1 Efficient Market Hypothesis

The Efficient Market Hypothesis was first presented by Eugene Fama in 1970. Efficient Market Hypothesis argues that the market is efficient when prices reflect all the available information. Fama (1970) uses words “fully reflect”. In a Market where the price fully reflects all information, the information should be freely available without delay. The prices should provide accurate signals at any time and for any security chosen. When the market is efficient the prices also reflect investors’ expectations of the future. EMH has three forms. The first form is the weak form, in which prices reflect only historical information. The second form is the semi-strong form, in which prices reflect information that is public. The third form is the strong form, in which prices reflect information that isn’t public.

When the information is available to all without a cost, it should be reflected in the prices almost without delay. Hedge funds create returns by exploiting anomalies and mispricing’s. This shouldn’t be possible if prices truly reflect all available information. The financial market prices according to available information and as new information becomes available it can be seen in the prices almost immediately. This makes persistent risk-adjusted alpha unlikely.

Fama (1970) states the conditions for the market for the theory to hold. A fully efficient market would need to be free of all transaction cost, and all information should be available to everyone without a cost. In addition to those investors should agree on the implications of current information to current prices and distributions of future prices. Fama (1970) notes that the markets met in practice do not meet these conditions. For example, markets have transactional costs, and investors can gain new information by doing costly searches. Investors fail to meet the standards needed for the market to be efficient. Investors can often be irrational. The defenders of the EMH argue that there are limits to the effect of irrational investors. For example, Lo (2004, p. 18) argues that the effect would disappear over time due to the efficiency of the market.

Andrew Lo (1999, as cited in Lo, 2004) describes the efficient market hypothesis by using the three P's. Lo has derived the three Ps in "The Three P's of Total Risk Management" (1999). Three P's include : price, probabilities, and preferences. Lo uses these P's to break down the EMH. EMH isn't just one hypothesis, but it consists of many parts. Prices reflect the available information. Profits are random and reflected by probabilities. Preferences mean that investors act rationally based on their preferences.

The efficient market hypothesis has been the dominant theory in the financial industry for a long time. EMH can be seen as the baseline. Fama (1970) emphasizes that you cannot win the market. Keeping the efficient market hypothesis at mind when looking at the possible advantages of adopting artificial intelligence in strategies, it would be logical that it wouldn't bring excess returns. It could be argued that AI streamlines efficiency and the information would be seen in the prices even faster. Artificial intelligence could expedite the processing of information.

The EMH argues against hedge funds. The hedge fund industry relies on persistent excess returns. One possibility is that EMH is false and hedge funds actually manage to exploit the market's inefficiency. However, this fails to explain the high failure rate in the industry, periods of underperformance, or capacity constraints. Another possibility is that EMH holds and hedge funds create alpha by taking on additional sources of risk.

2.2 Adaptive Market Hypothesis

EMH depends on the assumption that the markets are efficient, information is freely available, and the information is always fully reflected in the prices. Thus, excess returns would be unattainable. "Therefore, no profits can be garnered from information-based trading because such profits must have already been captured" (Lo, 2004, p.16). This Lo's view of EMH creates room for another interpretation because hedge funds can survive and are affected by changes in market conditions.

Andrew Lo proposes an addition to the EMH. Lo describes AMH as "an evolutionary approach to economic interaction" (2004, p. 15). The Adaptive market hypothesis assumes that financial markets are evolutionary. Lo doesn't contradict the EMH as a whole but sees markets as more complex. Lo sees that EMH and it's contradictions and behavioral aspects can be combined to create a new synthesis: AMH (2004, p.21). Market behavior shapes financial markets in a way that can be compared to natural selection.

Markets must evolve to survive, and hedge funds showcase this. Competition, technology, and behavior change the markets. An evolutionary view can also be seen in other financial contexts (Lo, 2004, p. 22). Lo himself (2012, as cited in Getmansky et al., 2015, p. 97) describes hedge funds as the "Galapagos Islands of the financial sector". By this Lo means that hedge funds can be seen as the test sample for evolutionary thinking in the financial industry. Hedge funds are known for constantly adapting new techniques and new technology. Short lifespan is also characteristic of hedge funds. Returns are cyclical and tied to the ongoing situation.

Hedge fund returns are consistent with the AMH. AMH is capable of explaining returns and the cyclicality. “Empirical support for the AMH as it applies to the hedge- fund industry can be found in the dynamics of hedge-fund births and deaths” (Getmansky, 2015, p.99). When a hedge fund finds alpha, they exploit it until the market has evolved and that opportunity has diminished. Lo describes that cycles of profitability and loss are a sign of the market evolving (2004, p. 23). AMH also provides a framework for interpreting the role of artificial intelligence in the hedge fund industry. Artificial intelligence can be used to assist in alpha creation. Artificial intelligence is a comparatively new phenomenon and may create a competitive advantage. However, this advantage will erode as the market evolves and the use of AI becomes more widespread. Artificial intelligence can be seen as the new evolutionary mutation.

2.2.1 Behavioral Finance

Many economic theories have been criticized for their strict assumptions. Theories like EMH and CAPM rely on investors being rational (Sent, 2018, p. 1371). The notion is that people react consistently to information. Rationality is not a fact but a basic assumption. Behavioral finance finds systematic differences that don’t rely on rational decision-making. Bounded rationality seems to be closer to the truth. Bounded rationality refers to idea that individuals seek to make rational decisions but fail to do so because of cognitive constraints. Humans have narrow cognitive abilities, which affect their problem-solving abilities (2018, p. 1374).

The concept of bounded rationality gives an explanation for why individuals deviate from rational behavior. To understand this phenomenon more its important to know popular decision biases. One popular bias is *self-deception*. In self-deception an individual interprets the information in a way that is to their liking. This action maintains self-esteem by avoiding reality (Hirshleifer, 2001, p. 11). *Anchoring* refers to the phenomenon that people are influenced by information that is clearly uninformative (Tversky and Kahneman, 1974, as cited in Hirshleifer, 2001, p. 11). The third well known bias is the *gambler's fallacy*. Hirshleifer (2001) describes it as a belief that a recent occurrence of one outcome increases the odds that the next outcome is different. These biases may cause in a larger scale possible arbitrage opportunities.

Arbitrage plays a central role in market pricing. Irrational investor behavior and behavioral biases cause deviations in the market price. Shleifer & Vishny (1997, p. 35) describe arbitrage as "the simultaneous purchase and sale of the same, or essentially similar security in two different markets for advantageously different prices". This creates arbitrage opportunities. Studies show that arbitrage is not always able to fix all mispricings immediately and some persist over time. Researchers have found limits to arbitrage. Shleifer & Vishny (1997) suggest that arbitrage opportunities can be exploited only by a small number of investors who use other people's capital. Many arbitrage opportunities may seem straightforward at first but involve risks and constraints. Shleifer & Vishny (1997, p. 36) see that the little traders are usually not the ones who have the information and capabilities. In addition to that, arbitrageurs avoiding volatility explain the persistence in excess returns. Reasons mentioned above and other constraints show that there are limits to arbitrage.

Artificial intelligence can be utilized in many ways to lessen the effects of individual errors. Individuals have bounded rationality. Artificial intelligence can lessen cognitive constraints. Machine learning is able to systematically exploit arbitrage opportunities. Artificial intelligence could help individuals do the same. On the other hand, the market isn't entirely automated. Sent (2018, p. 1374) describes how individuals have self-control problems and, tend to focus on the short-term return rather than the long-term return. Artificial intelligence can function without self-control problems. But as said, the market isn't fully automated and has individuals who are affected by bounded rationality and heuristic biases.

2.3 EMH vs. AMH

This part contrasts the efficient market hypothesis and the adaptive market hypothesis. The objective is to prove their relevance to hedge fund alpha generation and their relationship to one another. As discussed, the adaptive market hypothesis doesn't invalidate the efficient market hypothesis but builds on it. The key difference between the two hypotheses is the concept of market efficiency. Fama (1970) assumes in the efficient market hypothesis that the market reflects all the available information, thus being perfectly efficient. Lo (2004) describes market efficiency in the adaptive market hypothesis as evolving and dynamic.

The discussion between the efficient market hypothesis and the adaptive market hypothesis is relevant to hedge funds, considering that hedge fund returns are based on market inefficiencies and anomalies. The efficient market hypothesis and the adaptive market hypothesis disagree on the existence of market inefficiencies. Under the efficient market hypothesis, there shouldn't be risk-adjusted returns. On the contradiction, within the adaptive market hypothesis framework, alpha can exist.

The adaptive market hypothesis framework is particularly relevant in the context of artificial intelligence. Artificial intelligence helps in the alpha creation by finding new anomalies. These anomalies don't persist since the market adapts to them. Artificial intelligence could make the market more efficient by finding anomalies and making the market adjust to them at a rapid pace. The adaptive market hypothesis aligns more closely with the phenomenon that can be seen in the literature.

2.4 Modern Portfolio Theory

Portfolio theory defines risk and expected return. Modern portfolio theory sees portfolios as a whole and not individual investments. Selecting a portfolio consists of two steps. Markowitz (1952) divides selecting a portfolio into two steps. The first step is observing stocks and creating observations. The second stage focuses on choosing a portfolio (1952, p.77). Markowitz (1952) describes how investors should strive to maximize expected returns and minimize risk. Expected returns simply mean the expectations of future returns and risk refers to the variance. Choosing different noncorrelating assets that have high expected returns, and low variance guarantees low portfolio risk. Given these beliefs, investors choose the best asset.

Portfolio theory can be expanded to modern portfolio theory. Sharpe (1964) extended portfolio theory by utilizing the concept of equilibrium. Thus, forming modern portfolio theory. Modern portfolio theory distinguishes excess return from expected return. Sharpe (1964, p. 425) explains the relationship between risk and excess return. More in depth it describes how much the return should increase when taking on additional risk. Being able to define excess return, otherwise known as alpha is fundamental for hedge fund research.

Markowitz (1952) provides a foundation for understanding how investors build optimal portfolios. In an optimal portfolio, the risk and return are balanced. Investors strive to maximize profit at a specific risk level. Sharpe (1964) describes all rational investors having the same optimal portfolio. This idea creates the idea of a market portfolio and its value is directly derived from its relation to the market. CAPM is based on this idea. If returns are greater than can be calculated using the CAPM, there is alpha.

2.4.1 Alpha Formula (CAPM-based)

$$\boldsymbol{R_e = R_f + \beta(R_m - R_f)}$$

In a simple way CAPM can be explained as risk-free rate + beta x (the expected return of the market – risk-free rate. Beta is the investment's sensitivity to the changes in the market. The value of beta tells how an investment moves in relation to the market. This is particularly fundamental with hedge funds, because hedge funds pursue positive returns regardless of market direction, regardless of the beta. CAPM is a way to calculate the expected return of an investment vehicle. When taking the risk-free rate from the expected return of the market, you get the risk premium. Risk premium reflects the additional value you get by taking on extra risk compared to a market-neutral investment.

The capital asset pricing model, CAPM is a starting point for defining alpha. CAPM is the most popular and uncomplicated way to assess alpha. Sullivan (2019, p. 2) describes alpha as the component that cannot be explained by risk premia. This is a definition straight from CAPM. According to CAPM, all returns should be able to be explained by the risk premia. Risk premia means the risk-free rate and the market risk combined. Part of the returns that cannot be explained by risk premia is alpha. There are many other models to assess alpha such as Fama-French and other multifactor models. CAPM can be considered to be the theoretical starting point when estimating alpha.

CAPM is easy to interpret, so investors are likely to use it as a tool to assess if the fund is creating extra value. Agarwal et al. (2018, p.18) concluded that CAPM best guides the investors even when compared to more complicated models. This could exaggerate the proportion of actual alpha. Multifactor models work in the same principle as the CAPM model. The return that cannot be explained by the factors is classified as alpha. With multifactor models, alpha is usually smaller but better defined.

3 Literature Review

Alpha is the cornerstone of hedge funds. Sullivan (2019, p.3) does a regression measuring hedge fund alpha and beta with the sample being from 1994 to 2019. Alpha varies over time, but the average per year is 1.7%. This shows that alpha is perpetual and not only a coincidence. Getmansky et al. (2015) define alpha as "the unique investment skills of the hedge fund manager". Recent developments indicate that this may no longer be supported by the current evidence. Analyzing alpha has the challenge of the hedge fund indexes having reliable data only starting in the 1990s (Fung and Hsieh, 2004, p. 66). A hedge fund index collects returns from several hedge funds and by doing that it creates a comparable indicator.

Prior literature has shown that artificial intelligence and technology have a significant i mpact on the financial industry. Grobys et al. (2022) distinguished 36 funds out of 826 using either AI or ML. This number is to grow with the possibilities of generative AI. Sheng et al. (2025, p.23) see hedge funds as pioneers of applying machine learning and AI to processes and strategies. Thus, meaning there is no historical data or comparable scenarios and it's hard to establish presumptions. Sheng et al. (2025, p. 34) can demonstrate that generative AI adoption had a large jump in 2022. This surge continues to the year 2023, in which it is even more pronounced. The jump can be tied to the release of GPT in March 2022 and to GPT 3.5 being introduced to the public in November of the same year. Before this jump, AI adoption was experiencing modest growth but was relatively stable from 2016 to 2021 (Sheng et al., 2025, p. 16).

AIMA's survey (2024) explains hedge funds' usage of AI. The report is called Getting in Polet Position: How Hedge Funds Are Leveraging Gen AI to Get Ahead. The survey in question was conducted during the fourth quarter of 2023 and there were 157 respondents responsible for $783 billion. This would mean that the average amount of assets under management was $5 billion. The survey shows that 86% of manager respondents allow their staff to use generative AI tools while working. Relevant to the hypotheses is how AI is implemented in practice. The survey also shows that the expectations on AI tools differ.

In contrast to generative AI, quantitative models and machine learning have been applied to the asset management industry for years. In 2016, approximately 9 percent of hedge funds used computer models for most of their trades and that 9 percent is estimated to be worth about $197 billion (Kaal, 2019, p. 7). Grobys et al. (2022) findings indicate that the percentage has grown considerably in recent years. The increasing adoption of new technology may support the hypothesis that AI is a new source for alpha. At the same time, the growing use of AI may increase competition, thus supporting the hypothesis that AI erodes alpha. Machine learning can be used to analyze data, correct supply and demand imbalances, estimate market movements, or even execute trades (Grobys et al., 2022). Aima's report (2024) shows that gen AI tools are used to enhance marketing materials, support coding efforts and for general research purposes.

Harvey, Rattay, Sinclair and Van Hemert (2017) researched the difference in excess return in systematic funds vs. Discretionary funds. Systematic funds apply strategies that are rule-based and have minimal daily human involvement. Discretionary funds are more traditional and operations are run by humans. Harvey et al. (2017) study had a baseline case specification that considered many factors, such as, dynamic, traditional, S&P 500 vol factors. Returns that couldn't be explained by these factors were considered to be alpha. Systematic funds were able to create more risk-adjusted returns than discretionary funds. For discretionary macro funds, the excess return was 2.86% while for systematic macro funds it was 4.85%. Harvey et al. (2017) explain this difference by saying that macro funds take more volatile positions. The findings are not directly comparable since Harvey et al. (2017) discuss mutual systematic funds and not artificial intelligence hedge funds. However, the findings might indirectly support the hypothesis that AI can create alpha by showing that quantitatively driven funds can have advantages over traditional approaches.

Harvey et al. (2017) observe that with equity mutual funds, discretionary funds outperform systematic. This finding may suggest that discretionary funds may be able to generate higher excess returns in certain market segments and systematic funds in others. With all factors taken into consideration, systematic equity funds produced and alpha of 1.11% and discretionary equity funds produced an alpha of 1.22%. With macro funds, systematic funds outperformed and with equity funds systematic funds struggled. Harvey et al. (2017) conclude that some market inefficiencies are better exploited by a discretionary approach. The mixed findings imply that technology driven investing doesn’t always outperform.

3.1 Hedge Fund Returns

The hedge fund industry has been growing rapidly since the 1990s, when people wanted to find alternative investment vehicles. The rapid growth has sparked interest from researchers. For example, given that hedge fund returns don’t follow normal distribution intrigues researchers. Hedge funds also interest investors seeking market-neutral alternative investments that can produce returns in the “high single-digit to low-double-digit range” (Kao, 2002, p.16)

As noted earlier, a hedge fund’s returns consist of beta and alpha. Getmansky et al. (2015, p. 107) define alpha as ”an active return on an investment” and beta as ”systematic risk of a stock or portfolio with respect to the market as a whole”. Getmansky et al. (2015) decompose the returns into three categories: fees, beta and alpha. Beta is generally considered easier to analyze since it is associated with systematic risk and the overall market development. Compared to beta, alpha is inherently more challenging to analyze due to its complexity. Assets under management in the hedge fund industry are almost four trillion dollars, and there are approximately 18,000 active hedge fund managers (Grobys et al., 2022, p. 4632). Despite the size of the industry, hedge funds can create alpha, and this has gained academic interest.

According to Fung and Hsieh (2004) hedge fund returns differ from those that come from mutual funds. Agarwal et al. (2018) further emphasize the differences with characteristics that differ. One notable distinction is that hedge funds charge a performance-based incentive fee. Hedge funds have described this fee as a price for the unique sources of returns hedge funds claim to have. Getmansky et al. (2015) further elaborate on the differences by identifying more characteristics that differentiate hedge funds from mutual funds. For example, hedge funds take on more risk than mutual funds. Hedge fund strategies are also often heavily leveraged to boost returns. Viebig (2012) emphasizes the role of leveraged strategies, noting that they can have a huge effect on the profit, but when the market suffers losses can also be substantial.

Kao (2002) discusses hedge fund biases such as survivorship, self-delisting, selection and back-filling. These biases occur because there isn't a performance measure framework. Survivorship bias is widespread in the hedge fund industry. It means that attention is paid only to funds that survive and not to the ones that fail. The impact of survivorship bias is further highlighted by Viebig (2012), who emphasizes the short lifespan of hedge funds. Half of hedge funds perish within five and a half years of creation. When studying only the hedge funds that are still operating, it makes the results seem better than they are. Self-delisting means that a hedge fund stops reporting voluntarily. This can be attributed to periods of weak performance. Self-delisting bias has the same consequence as survivorship bias. Selection bias also has the same outcome. Funds that are doing well are more likely to start reporting to present evidence of success. Back-filling bias means that hedge funds can fill in past returns after joining the database.

Viebig (2012) explains how hedge funds are not compelled to report routinely, because they are mostly unregulated. The Reporting is completely voluntary, and the databases are not regulated. This creates difficulty in analyzing returns properly. As discussed above hedge fund statistics should be considered definitive. Biases make reports and indexes untrustworthy. Getmansky et al. (2015) further argue how hedge fund biases reinforce historical estimates of expected returns and at the same time reduce predicted variance and covariances. The dampened variance and covariance are a result of autocorrelation. Autocorrelation means that when hedge funds have illiquid assets in their portfolio, the assets aren't priced daily. This makes the returns seem steadier. Fung and Hsieh (2004) agree that the absence of a performance-reporting standard makes it difficult to define expectations for performance.

Kao (2002) examines the determinants of superior performance compared to other investment vehicles, especially compared to long-only portfolios. Kao (2002, p. 23) mentions four reasons: data accuracy, compensation differences, investment restraints and differences in structure. The loose regulations allow these. Many biases distort the data. Distortion of data creates the illusion that the returns are better than they are. Compensation differences mean that hedge funds collect the performance fee which motivates the managers. Investments don't have restrictions and structure isn't pre-dictated. All these differences reflect the reasons why hedge funds can create alpha.

Sullivan (2019, p. 7) raises the question of how much of hedge fund returns can be explained by risk factors and how much of it comes from the nature of hedge funds. Capital asset pricing model, CAPM, explains returns with the market risk. Other risk factor models take into consideration many factors. Risk factors include value, size, momentum, volatility, liquidity and carry, among others. The Fama-French asset pricing model considers three factors: market risk, size and value. Models like the Fung-Hsieh Seven-Factor model consider even more factors to define returns more precisely. When calculating alpha with a multifactor model, alpha is the part that isn't attributable to factors. Alpha's significance can be proven by alpha remaining significant when calculated with CAPM and also with some multifactor model. Often the so-called alpha diminishes when applied to a multifactor model. Thus, being beta. Consequently, this complicates analyzing the impact of artificial intelligence.

Cochrane (2011, as cited in Agarwal et al., 2018, p. 1) describes a conversation with a hedge fund manager who claims "exotic beta" is his alpha. The hedge fund manager goes further and explains that he understands exotic factors and can use them, but his clients don't. This highlights the relationship between alpha and beta. Earlier all returns unrelated to market have been explained as alpha, now traditional risk factors and exotic risk factors have also been identified (Agarwal et al., 2018, p. 1). Hedge funds offer investors these untraditional returns.

Fung and Hsieh (2004, p. 71) have created the seven-factor model. They found that 57% of hedge funds in TASS and 37% funds in HFR had these seven risk factors. TASS and HFR are hedge fund databases. This finding suggests that a big part of the alpha hedge funds have is a consequence of the risk factors. Thus, multifactor models reveal that much of the excess return comes from risk positions. Fung and Hsieh (2004) believe that future research will find more risk factors.

Hedge funds offer higher risk-adjusted expected returns; diversity in assets, market and styles and fewer constraints on portfolio managers to encourage them to create unique sources of alpha (Getmansky et al., 2015, p.1). In addition to average market returns, hedge funds can create risk-adjusted excess returns. That is what makes hedge funds unique compared to mutual funds. The unique talent has created a large industry around it. For example, Citadel, Bridgewater Associates, Man Group Ltd and AQR Capital Management are well-known hedge funds. “We will explore any territory in pursuit of an idea, taking unconventional approaches and making big, bold investments in unexpected places” (Citadel, 2025). This quote from Citadel is a reflection of hedge funds.

The literature presents a few issues with exploring hedge funds. To find evidence for the first hypothesis, it would need an extensive amount of accurate historical data. To state that artificial intelligence is a new source for alpha, one should be able to verify the historical sources of alpha and be able to identify alpha from beta. The unique characteristics and the reporting system make research complex.

3.2 Shift in sources of alpha

Sullivan (2019, p.25) describes a change in alpha creation. 15 years leading up to the financial crisis, hedge fund performance was strong and hedge fund managers were able to add 3.4% per year risk-adjusted return on average. 10 years after the financial crisis the comparable number is –1%. This could indicate a large-scale change in return creation. Kao (2002) emphasizes the nature of the hedge fund industry. Hedge funds operate in a loosely defined operating environment, thus making returns and their creation process hard to analyze. The change in sources should be examined through the broader structural change.

Kaal (2019, p.3) cites 2018 Barclay Hedge survey and states that 56% of hedge funds use either AI or ML in decision making or generating ideas and a quarter of survey respondents use AI or ML for trade execution. The survey results show that the industry is adapting to new technologies. Kaal (2019, p. 5) describes the core technologies adopted by hedge funds as "semiconductors to increase trade execution, artificial intelligence to optimize data models, big data applications to facilitate unprecedented trend analysis". These technologies offer an alternative method to conduct trades. Kaal (2019) also sees the use of financial technology in hedge funds as diverse and constantly evolving.

One example of AI adaptation in daily functions is Numerai. As Kaal (2019, p. 11-12) states, Numerai is a private investment fund. Numerai uses artificial intelligence in data handling. The data is processed and converted to machine learning problems that data scientists solve. This streamlines efficiency and optimizes capital allocation. Further in the Numerai model, execution is aided by real-time data, algorithms and direct market access. Kaal (2019, p. 8-9) presents ways AI technology can be applied to streamline efficiency. Natural language processing and robotic process automation for simple processes and data handling are already happening with the help of AI. Kaal (2019) argues that AI has provided easier access to trading data and that has caused growth in hedge fund assets. Kaal (2019) believes advanced AI technology could help establish new revenue streams.

Sheng et al. (2025) propose a measure for investment companies, reliance on artificial intelligence. This measure is called RAI. Sheng et al. (2025) measure RAI through the responsiveness of hedge fund portfolios to AI-predicted signals. RAI experienced rapid growth in 2022. This growth aligns with improvements in generative AI. This surge in RAI in 2022 can be combined with the introduction of ChatGPT. The introduction of ChatGPT changed generative AI from a rare competitive advantage to something that can be widely exploited. The association between RAI and hedge fund returns could imply that generative artificial intelligence itself is a new source of alpha, thus supporting the second hypothesis.

Kao (2002, p. 20), while looking for the best sources of alpha, points out that the source of alpha changes when changing the asset, the strategy and market. For example, sources of alpha are different whether looking at equity market-neutral funds or fixed-income arbitrage funds. The amount of alpha is strongly affected by competition and as investors enter the alpha can erode. Unlike alpha, beta, true factor premia does not decay in the same way as alpha. Beta is based on risk factors. Israel et al. (2020) further suggest that machine learning can help in value creation, for example, by finding suitable combinations of risk factors.

Harvey (2017, p. 3) notes that systematic funds show dispersion similar to that in discretionary funds. This contradicts the assumption that systematic funds are homogeneous. Grobys et al. (2022) identify AIML funds as a distinct category from systematic and discretionary funds. The difference is that AIML funds don’t need to find the optimal level of human involvement. Thus, avoiding behavioral biases. The difference from systematic funds is the AIML fund’s ability to learn and adapt. Artificial intelligence models excel at asset price forecasting and finding patterns in data. Being able to find unique patterns might lead to the creation of strategies that human hedge fund managers aren’t able to see (Gerlein et al. (2016, as cited in Grobys et al., 2022, p.

4635). Together, these findings align with the second hypothesis. AI-driven approaches may be able to generate alpha by exploiting previously unnoticed opportunities.

Strategy distinctiveness is associated with higher returns. Traditional strategies are easier to copy. Thus, making the strategy crowded and losing the alpha (Sun, Wang & Zheng, 2012, as cited in Getmansky et al., 2015). AIML funds have distinctively different investing strategies compared to traditional funds. These unique strategies are hard to scale up but also hard to replicate (Grobys et al., 2022, p. 4635-4640).

Kao (2002, p.17) states that hedge funds are usually divided into categories by their trading styles, but despite many attempts, there are no clear standards for that. Not being able to categorize comes from the difficulties of hedge fund research. As noted, the hedge fund industry isn't heavily regulated and reporting is voluntary. Another noteworthy feature about hedge funds is their short lifespan. Getmansky et al. (2015) state that half of hedge funds don't survive to their fifth anniversary and only 40% of hedge funds survive for 7 years or longer. The early years of the hedge fund lifecycle are important for future success. The short lifetime is a consequence of the high competition that hedge funds have. The hedge fund industry is a major industry, and all are eager to produce alpha. Those who can't generate alpha will fail. Hedge funds shift trading positions and exposures to risk factors often. Hedge funds need to change positions rapidly to find alpha, as when strategies get crowded, the alpha diminishes. Strategies aren't persistent as alpha erodes over time. Sources of alpha are dynamic and constantly changing (Kao, 2002, p. 25). Constantly changing strategies could also imply constantly changing sources for alpha.

Fung and Hsieh (2004, p.79) analyze how the seven factors in their seven-factor model explain a large part of the returns. Harvey et al. (2017) demonstrate that discretionary funds show a stronger exposure to well-known risk factors in asset pricing models compared to other funds. Grobys et al. (2022, p. 4633) find that the returns of highly automated hedge funds lack correlations with risk factors such as size, profitability and momentum. In contrast, Grobys et al. (2022) find that the hedge funds that exhibit the highest level of human involvement in the decision-making process invest in unprofitable “loser stocks”. Overall, the literature suggests that hedge fund returns are closely related to factor exposures.

Sullivan (2019) describes how hedge funds’ ways to produce excess returns were limited. Now, hedge fund managers can use several risk factors to their advantage to produce returns. Hedge fund managers’ ways to generate excess returns are not restricted only to idiosyncratic alpha. This could indicate that sources of alpha have shifted to be more systematic. Agarwal, Green and Ren (2018) go further and say that investors give credit to hedge fund managers not only for producing alpha but also for creating returns through exposure to exotic risk.

Kaal (2019) states that AI technology can be used to automate processes and to create new revenue streams. This entails that AI, and especially generative AI, is creating new sources of alpha. Generative AI is able to create strategies that human hedge fund managers can’t. This creates a competitive advantage by being distinctive. The distinctiveness of a strategy is crucial for making excess returns. Sheng et al. (2025) show that RAI has grown rapidly. This entails that the industry is going through a change. This change could also signify a change in the sources of alpha. Grobys et al. (2022) findings about different types of funds correlating with different risk factors show that the structure of returns varies in different funds. The returns being different and funds correlating with different risk factors could also imply that the source is different. This raises the question of whether the uniqueness of a strategy is an implication of an alpha source being unique. These findings seem compatible with the second hypothesis.

3.3 Does AI Create or Erode Alpha?

Noted in the chapter before, there is evidence that the recorded alpha has declined. Sullivan (2019, p. 1) argues that hedge funds as a group have shown a decline in risk-adjusted alpha in the ten years following the financial crisis, stating that hedge fund managers have underperformed the stock market ever since the financial crisis. The extent of risk-adjusted alpha depends on the method used for calculating. Experts' opinions differ on what is the appropriate way. Getmansky et al. (2015) disagree and argue that it is apparent that hedge funds aren't a temporary phenomenon since they have shown a persistent alpha. Sullivan (2019) goes on and argues that the decline in alpha has led to the question of whether alpha has disappeared altogether. The literature presents mixed findings regarding the persistence of alpha.

The amount of risk-adjusted alpha depends on its calculation methodology and experts' opinions differ on what is the best method. Getmansky et al. (2015) disagree and argue that it is apparent that hedge funds aren't just a passing anomaly, since hedge funds have shown persistent alpha. Sullivan (2019) goes on to state that the decline in alpha has led to the question of whether alpha has disappeared altogether. The literature presents mixed findings regarding alpha persistence.

Sullivan (2019, p. 7) speculated that the ability to produce alpha has greatly reduced due to the forces of arbitrage. Making the alpha after fees only a zero. Fung and Hsieh (2004) go further and argue that there is a decline in hedge fund alpha long before the financial crisis. Sullivan (2019) concludes that the forces of arbitrage have made more managers seek alpha, which has led to the erosion of alpha. This aligns with the discussion of the erosion of alpha but does not suggest that the erosion process is driven by artificial intelligence.

Fung and Hsieh (2004, p. 73-76) describe alpha vanishing long before the financial crisis or the adaptation of artificial intelligence. Comparing hedge funds in two subperiods, they find that in the second period**,** excess returns created by the fund manager declined rapidly. The returns can be explained by the systematic risk factors. Thus, being beta. Also, hedge fund indexes show a decline in the amount of alpha in the second period. They make a connection between the first period's better alpha and the bull market. Implying that the alpha that can be seen in the first period is a result of a favorable market.

In contrast, Getmansky et al. (2015) don't find evidence of alpha systematically declining, but notes that the amount of alpha fluctuates based on the market environment. Billio, Frattarolo and Pelizzon (2014, as cited in Getmansky et al., 2015, p. 21) find that in a large sample, alpha fluctuates over time. They connect this to the competition among hedge funds. Goetzmann, Ingersoll, and Ross (2003, as cited in Getmansky et al., 2015, p. 8) propose that the reason successful hedge funds aren't always willing to accept new money is that there is fear of diminishing returns. If there is too much money after the same alpha, it could get crowded and diminish. Sun, Wang, and Zheng (2012, as cited in Getmansky et al, 2015, p. 22) report that hedge fund success is associated with strategy distinctiveness. If a hedge fund uses generative AI as its way to stand out and outperform competitors. This raises the question of what happens when the competitors also start using generative AI. Consistent with previous statements, Israel et al. (2020) point out that as more investors enter the market using similar data and artificial intelligence, the inefficiencies in the market correct themselves and alpha diminishes. These findings are consistent with the first hypothesis. Artificial intelligence causing increasing competition, could erode alpha.

Harvey et al. (2017, p. 10-12) show that both discretionary macro funds and systematic macro funds can produce alpha. Systematic macro funds created a risk-adjusted alpha of 4.85% and discretionary macro funds created an alpha of 1.57%. Showing that in macro funds, a systematic approach managed to create better results than a discretionary approach. Harvey et al. (2017) find that both approaches were able to produce alpha, providing evidence that there is alpha to be found. Harvey et al. (2017, p. 14) make it clear that the finding shouldn't be interpreted to imply that systematic funds are naturally superior to discretionary funds. Discretionary equity funds can create a bigger risk-adjusted alpha of 1.22% when systematic equity funds create an alpha of 1.11%. Harvey et al. (2017) key findings were that some market inefficiencies are better exploited by systematic approaches and others by discretionary approaches. These findings contradict the first hypothesis by showing that there is alpha.

In contrast to previous literature, Sheng et al. (2025) report that hedge funds with higher RAI also generate significantly higher risk-adjusted returns, increasing the importance of technology. Kaal (2019) agrees and states that the hedge fund strategies that are based on AI have produced better results than the average over the last five years. Kaal (2019) presents evidence that AIML funds perform better than traditional funds. Sheng et al. (2025) highlight how information is key to success in the asset management industry. AI or ML can effectively be utilized to expedite the retrieval of information. Grobys et al. (2022) propose that when using AI systems, hedge funds can avoid behavioral bias, unlike humans. Thus, creating better alpha than a human hedge fund manager. These findings are consistent with the second hypothesis that AI is an alpha source. At the same time, these findings contradict the first hypothesis and prior literature.

The literature presents differing views about alpha's possible deterioration. There seem to be a few main opinions on the topic. One is to argue that alpha has been in decline since the financial crisis or even longer. Second is to deny the whole existence of alpha. Third is to say there is no decline and the alpha is just cyclical. The literature supports the idea that alpha isn't constant over time. Regarding alpha's persistence performance, the evidence suggests that returns persist for short periods but disappear in the long run. Persistence is tied to past performance. A hedge fund is more likely to produce alpha in the next two years if it has produced alpha in the past two years. Additionally, superior hedge funds showcase greater persistence compared to inferior funds (Getmansky et al., 2015, p. 24). Sheng et al. (2025) and Kaal (2019) produce evidence for the second hypothesis. They are able to show that artificial intelligence can be used and is used to create superior risk-adjusted returns compared to the competition. Harvey et al. (2017) don't find an explicit connection with technology and greater alpha, but connect it with what market inefficiency is exploited and with what approach. Israel et al. (2020) findings correlate with the first hypothesis. Competition makes mispricing correct faster and consequently compresses the alpha.

3.4 Is Alpha a Measure of Skill or Technology?

Alpha is the cornerstone of hedge funds. Sullivan (2019, p.3) does a regression measuring hedge fund alpha and beta with the sample being from 1994 to 2019. Alpha varies over time, but the average per year is 1.7%. This shows that alpha is perpetual and not only a coincidence. Getmansky et al. (2015) define alpha as "the unique investment skills of the hedge fund manager". Analyzing alpha has the challenge of the hedge fund indexes having reliable data only starting from the 1990s (Fung and Hsieh, 2004, p. 66). A hedge fund index collects returns from several hedge funds and thereby creates a comparable indicator.

Hedge fund characteristics come from "managerial incentive structures, managers' ability to hedge, strategy distinctiveness, connections with political lobbyists, education and career concerns, confidential holdings, delayed reporting, managerial skills, and capacity constraints" (Getmansky et al., 2015, p. 20). This is a traditional way to look at the sources of alpha. "These results can be interpreted in at least two ways: managerial alpha is, in fact attributable to "exotic betas", or hedge fund managers generate alpha when macro conditions are conducive" (Getmansky et al., 2015, p. 22). Alpha is complex and not explicit. Identifying alpha from beta isn't straightforward. Getmansky et al. (2015, p. 22) go even further and cite studies linking alpha to even geography, career concerns, strategy capacity, political connections and managers' SAT scores.

Gerlein et al. (2016, as cited in Grobys et al., 2022, p. 4632) describe artificial as an evolutionary process that has the potential to replace the end user. Harvey et al. (2017,p.2) argue that algorithms are common with hedge funds, but the roles differ greatly depending on the fund. Kaal (2019, p. 6) describes that the technology used in hedge funds today is hard-coded by humans, but the AI solutions can work based on a given command and evolve. There already exist systems that are AI-based and work on the principle of analysis-to-decision-to-execution, meaning that the systems work independently from start to finish. In this type of system, the human role disappears. Kaal (2019) reviews ways machine learning can be used. It can make predictions on real-time information, analyze older data, predict cash flow and predict financial indicators based on past performance, accurately diversify a portfolio, generate investment strategies and analyze public statements, among others. These are just illustrative and, what's used in practice may differ.

Kaal (2019) states that hedge funds quickly adapting to AI technology is natural since hedge funds have pioneered the use of emerging technologies in the asset management industry. Pioneering new technologies and optimizing their performance gives a competitive edge. Kaal (2019, p. 24-25) describes a fully automated electronic trading platform. Aidyia, a Hong Kong-based hedge fund, has a fully automated trading system based on AI. This system uses probabilistic logic, deep learning and evolutionary computation. The system's logic is as follows: creating market predictions and then deciding the best course of action. The goal is to be able to recognize market changes and react accordingly. Kaal (2019) also describes a hedge fund called Sentient Technologies of San Francisco. This fund operates solely on AI. The system authorizes a strategy and then gives commands to hedge fund managers. The system works independently but allows the changing of risk settings. These fully automated funds contradict alpha being attributed from talent and support the second hypothesis.

Dalio (2017, as cited in Grobys et al., 2022, 4632) argues that the recent advances in machine learning can't be directly utilized and need a deeper understanding. Dalio (2017) describes machine learning developments as a data mining tool. It can be used to recognize patterns from a large data set, but finding a pattern does not necessarily mean finding a strategy. Gerlein (2016, as cited in Grobys et al., 2022, 4632) outlines artificial intelligence as an evolutionary process. Artificial intelligence started as simple automation but is constantly adapting and increasingly autonomous in decision-making. Dalio's (2017) views question the second hypothesis that AI would be a source of alpha.

AI systems aren't entirely independent. Sheng et al. (2025, p. 4) state that many of AI systems still require data and expertise. Algorithms need to be retrained to keep up with the market. Systems that use AI would need human involvement. Grobys et al.

(2022) propose that human involvement being needed could be fixed with generative AI. There can already be seen a connection between hedge fund returns and ChatGPT. ChatGPT is a type of generative artificial intelligence. Sheng et al. (2025, p.45) show a connection with the usage of generative AI and hedge fund returns and these findings support the second hypothesis.

Dietvorst, Simmons and Massey (2015, as cited in Grobys et al., 2022, p. 4634) report that some investors are averse to funds using new technology such as machine learning or artificial intelligence. The fears are related to using algorithms. This limits the AI adoption. Thus limiting its potential as an alpha creator. Grobys et al. (2022) introduce another limit with AIML funds. The unique AIML fund strategies are difficult to scale up. These limitations provide a counterargument to the second hypothesis. These findings could imply that AI-driven strategies may not consistently generate alpha.

Israel et al. (2020, p. 6) point out that machine learning works best in environments that have little noise and are data-rich with strong signals. This isn't the case with asset management. People's expectations for ML thrive from the examples of what have been done. People have high expectations that aren't met in practice. The first reason is small data. The number of observations the data has isn't able to support a model with only a few parameters. Machine learning isn't able to create results when there isn't enough data. The ML model would learn the training data, thus overfitting the data. Another reason why machine learning struggles in asset management is the low signal-to-noise ratio. Low signal-to-noise ratio follows the principles of the efficient market hypothesis. Israel et al. (2020, p.9) describe how investors with information exploit it until prices have been adjusted to the level the information predicts. If there is a signal, there is already someone exploiting it. This makes the financial industry hard to predict. Israel et al. (2020) findings challenge the second hypothesis.

"An interquartile increase in the reliance on generative AI is associated with gain of 3% to 5% in annualized abnormal returns" (Sheng, 2025, p. 4). This 3% to 5% growth in alpha was calculated with different asset pricing models, to ensure alpha wasn't caused by a fault in the model. Harvey et al. (2017) present systematic funds and discretionary funds performance having increasing similarities in the period from 1996 to 2014. These similarities support the idea that technological and AI-driven methods are becoming more important. Grobys et al. (2022) conduct a test by creating “a man-versus-machine" strategy which has long hedge on highly automated funds and short hedge with traditional funds. They find that hedge funds with the highest level of automation outperform other kinds of funds. Showing a correlation between automation and alpha. These findings support the second hypothesis while implying that alpha is at an increasing rate a result of technology.

AIML funds might be able to source unique trading opportunities better than systematic funds. AIML funds excel in finding patterns in data and that leads to creating different strategies than human traders. Some AI models don't need specific programming. Given a desired outcome, the model itself chooses the best course of action with the help of a mathematical function. Grobys et al. (2022) argue that AIML funds could perform better due to the unique strategies and partially independent systems. Grobys et al. (2022) find it surprising that funds that implement both, human expertise and machine learning underperform others.

Fung and Hsieh (2004, p.71) question the interpretation of alpha as skill. They report that the returns can be greatly explained by the seven-factor model. They found that from looking at two different databases, many hedge funds exhibit the risk factors. In one database, the risk factors were found in 57% and in another database, the factors were found in 37%. This questions the alpha being from managerial skill since alpha can be achieved by a systematic model. Grobys et al. (2022, p.4643) found using CAPM model, Fama & French's three-factor model and Carhart's four-factor model, that funds employing either artificial intelligence or machine learning generated better average returns compared to funds with more human involvement. Grobys et al. (2022) propose that if less direct interaction with trading and more control to algorithms yield better results, funds should start using fully automated decision-making. Harvey et al.

(2017, p.3) note that by simply implementing the factors, you will end up with negative alpha because you cannot produce factors at zero cost. Factors can help understand where the excess returns come from, but they don't necessarily lead to positive alpha. Hedge funds compete in producing factors as profitably as they can. To get positive risk-adjusted returns, it also requires managerial skill.

Alpha has been greatly connected to managerial skills and characteristics. For example, a greater alpha is connected to managerial incentives. Higher levels of ownership correspond to better risk-adjusted returns. Hedge fund managers' character traits are also connected to alpha. For example, educational background and career concerns can have a positive impact on performance (Getmansky, 2015, p. 22). Hedge fund managers have had a big role in the decision-making in hedge funds. The sparse data available was processed by hand with simple models. With machine learning, the process can be mechanized and algorithms can go through data fast. With ML, reactions to data are faster. ML makes it possible to take advantage of unstructured data (Israel et al., 2020, p. 17). These findings support the second hypothesis by showing that data-driven fund has a great ability to produce alpha.

4 Conclusion

This thesis examines the effects of artificial intelligence on hedge fund returns. Special focus is on the relationship between alpha and artificial intelligence. Furthermore, the relationship between alpha and beta and their qualities is investigated in depth. Hedge funds' unique characteristics are also noted. The theory section gives a comprehensive overview of a few theories that offer a perspective on hedge funds and return creation. The social significance of this topic is obvious as hedge funds manage trillions of dollars and have the ability to impact the whole economy.

Many studies are highly focused on distinguishing alpha from beta. The existence of alpha in hedge funds is argued. It is also essential in this context, but this thesis focuses more on the possible implications of the usage of artificial intelligence. The topic offers differing views on the impact of artificial intelligence. Artificial intelligence and more specifically, machine learning can be seen as a positive indicator for better returns. AI offers a new technological edge that benefits hedge fund managers. Then there is the separate matter of whether these increased returns are all part of alpha or are at least some of them attributable to risk factors. Multifactor models used today note several factors and, by doing so, give a fairly accurate description of what is beta and what is alpha. There is still room for improvement in that regard. As Fung and Hsieh (2004) pointed out, there are probably more factors to be found.

However, as noted, there are differing opinions on the topic. Some of the literature emphasizes the property of alpha to disappear when competition increases. To say artificial intelligence is causing the erosion of alpha it would require data from a longer period of time. The basic idea is that as more investors obtain the same or similar tools and data, the mispricing where the alpha comes from will correct itself. If artificial intelligence is used in return creation, the advantage it brings would get competed away as AI becomes more commonly available. This is something that should be observed over time.

Many of the findings support the second hypothesis. As finding market anomalies and mispricing's are crucial for creating alpha, AI can assist these efforts. Machine learning is able to find patterns in data that human hedge fund managers aren't able to see. In addition to finding the opportunities for alpha, it streamlines the whole process. Being able to find alpha opportunities and taking advantage of them faster than competitors contributes to higher returns. It cannot be concluded that the highest level of automation always correlates with the highest returns. Some of the literature supports the concept that some market inefficiencies are better exploited by discretionary approaches and others by systematic approaches. The first hypothesis is supported by the literature emphasizing the effect of competition on excess returns. Permanent disappearance or erosion of alpha cannot be proven. If evidence suggests that alpha is diminishing, it can be seen as part of the natural cycle. New anomalies and mispricings come up when an old one disappears.

The findings should be interpreted with caution, as hedge fund data isn't always reliable. Data concerning hedge fund returns have limitations since hedge funds aren't compelled to report routinely, and the data presents numerous distortions. The phenomenon of artificial intelligence and especially generative AI in hedge funds is moderately new. Thus, there isn't enough historical data.

There is room for future research on the impacts of artificial intelligence on alpha generation. The emphasis could be on the improvements of generative AI. Future research could focus on long-term implications. An empirical study should be carried out when there is enough historical data. Generative AI creates interesting opportunities for future research.

AIMA's survey (2024) uncovers the issues in AI adoption. The biggest challenges seem to be data security, inconsistent responses and the need for staff training. Future research could examine the need for education and the implications of staff having permission to use generative AI without proper training. In AIMA's survey (2024) 86% of hedge fund managers permit staff to use generative AI but only around 10% of survey respondents have received training on the use of generative AI.

References

Agarwal, V., Green T.C., Ren, H. (2018). Alpha or beta in the eye of the beholder: What drives hedge funds flows? *Journal of Financial Economics*, 127(3). https://doi.org/10.1016/j.fineco.2018.01.006

Citadel.(2025). What We Do. https://www.citadel.com/what-we-do/

Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance,* 25(2). https://doi.org/10.2307/2325486

Fung, W., Hsieh, D.A. (2004). Hedge Fund Benchmarks: A Risk-Based Approach. *Financial Analysts Journal,* 60(5*)*. https://doi.org/10.2469/faj.v60.n5.2657

Getmansky, M., Lee, P. A., Lo, A.W. (2015). Hedge Funds: A dynamic industry in transition. *Annual review of financial economics,* 7(1). https://doi.org/10.1146/annurev-financial-110311-101741

Grobys, K., Kolari, J., Niang, J. (2022). Man versus machine: on artificial intelligence and hedge funds performance. Applied Economics, 54(40). https://doi.org/10.1080/00036846.2022.2032585

Harvey, C.R., Rattray, S., Sinclair, A., Van Hemert, O. (2017). Man vs. Machine. Comparing Discretionary and Systematic Hedge Fund Performance. *Journal of Portfolio Management,* 43(4). https://doi.org/10.3905/jpm.2017.43.4.055

Hirshleifer, D. (2001). Investor psychology and asset pricing. *Journal of Finance,* 56(4). https://doi.org/10.1111/0022-1082.00379

Israel, R., Kelly, B. T., & Moskowitz, T. J. (2020). Can machines learn finance? Journal of Investment Management. https://doi.org/10.2139/ssrn.3624052

Kaal, W.A. (2019). Financial Technology and Hedge Funds. The Oxford Handbook of Hedge Funds. *Oxford University Press,* Chapter 10. https://doi.org/10.1093/oxfordhb/9780198840954.001.0001

Kao, D.-L. (2002). Battle for Alphas: Hedge Funds versus Long-only Portfolios. *Financial analysts journal,* 58(29). https://doi.org/10.2469/faj.v58.n2.2520

Lo, A. (2004). The Adaptive Market Hypothesis. The journal of portfolio management. https://doi.org/10.3905/jpm.2004.442611

Markowitz, H.M. (1952). Portfolio Selection. *The journal of finance,* 7(1). https://doi.org/10.1111/j.1540-6261.1952.tb01525.x

Sent, E-M. (2018). Rationality and bounded rationality: you can't have one without the other. *The European Journal of the History of Economic Thought,* 25(6). https://doi.org/10.1080/09672567.2018.1523206

Sharpe, W.F. (1964). Capital Asset Prices: A Theory of Market Equilibrium under conditions of risk. *The Journal of Finance,* 19(3). https://doi.org/10.2307/2977928

Sheng, J., Sun, Z., Yang, B., Zhang, A. (2025). Generative AI and Asset Management. *Review of Financial Studies* (forthcoming). SSRN working paper.

Shleifer, A., & Vishny, R.W. (1997). The limits of arbitrage. *Journal of Finance*, 52(1), 35-55. https://doi.org/10.1111/j.1540-6261.1997.tb03807.x

Sullivan, R. (2019). Twenty-Five Years of Hedge Fund Returns. The Journal of Alternative Investments (forthcoming). SSRN working paper. https://doi.org/10.2139/ssrn.3498595

Viebig, J.H., What do we know about the risk and return characteristics of hedge funds? *Journal of Derivatives & Hedge Funds, 18, 167-191 (2012)*. https://doi.org/10.1057/jdhf.2012.4